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**Dynamic Dispatching and
Repositioning Policies in Service
Logistics Networks**

by
Collin Drent

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Student identity number 0805771

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Supervisors:

prof.dr.ir. G.J. van Houtum, TU/e, OPAC

prof.dr. T. van Woensel, TU/e, OPAC

dr.ir. J.J. Arts, Université du Luxembourg, LCL

dr. M.C.A. Olde Keizer, CQM

dr.ir. J.B.M. van Doremalen, CQM

TUE. School of Industrial Engineering.
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Abstract

Motivated by the increasing demand for faster service when advanced capital goods fail, we address the problem of dispatching and pro-actively repositioning service engineers in a service logistics network such that extremely short solution times to service requests can be realized in a cost-efficient way. By formulating this problem as a Markov decision process, we are able to investigate the structure of the optimal policy, thereby focusing on specific characteristics of this optimal policy. Using these insights, we then propose scalable static and dynamic heuristics for both the dispatching and repositioning sub-problem for networks of industrial size, based on the minimum weighted bipartite matching problem and the maximum expected covering location problem, respectively. The dynamic dispatching heuristic takes into account real-time information about both the state of equipment and the fleet of service engineers, while the dynamic repositioning heuristic maximizes the expected weighted coverage of future service requests. In a test bed with a small network, we show that our most advanced heuristic performs excellent with an average optimality gap of 4.6% under specific circumstances, but strictly outperforms all other heuristics across all instances. To show the practical value of our proposed heuristics, we conducted extensive numerical experiments on a large test bed with networks of industrial size where significant savings of up to 61.9% compared to a benchmark static policy are attained. In the same test bed, we show that being flexible in deviating from previous dispatch and reposition decisions, regardless of the heuristics that are used for these decisions, can lead to substantial savings of 49.2% compared to when reallocation is not allowed. The results also show that using the proposed dynamic dispatching heuristic, instead of the widely adopted ‘closest-idle first’-heuristic, leads to savings of 27.7%.

Keywords:

Service logistics; Repair; Dynamic dispatching; Dynamic repositioning; Markov decision processes; Heuristics

Summary

For many manufacturers and service organizations, the availability of capital goods - such as MRI scanners, industrial printers or ATMs - is of crucial importance for their operations. Therefore, their uptime is of utmost importance; each minute of unplanned downtime may be costly, risky (in case of medical equipment), or both. As a result, the total unplanned downtime should be minimized. Many of these capital goods are maintained by means of a service logistics network, which is owned and managed by a service organization. Such a network typically consists of a single central warehouse and many service regions (mostly determined by geographical borders) in which the capital goods are installed (see Basten and Van Houtum (2014)). Generally, spare parts are kept on stock both in the central warehouse and in the vehicles of the service engineers that operate in service regions. Upon failure of a capital good, a service engineer is dispatched to this failed capital good if the problem cannot be solved remotely. A failure is often caused by a failed part which can then be replaced immediately by a new part if the dispatched service engineer has this part in its car stock, otherwise it is replaced in a second visit.

According to a recent survey among executives, one of the two top challenges for service organizations is the increasing demand from customers for shorter solution times (Pinder Jr, 2016). Furthermore, recent developments of communication networks and easy-to-integrate sensors allow service organizations to collect real-time data about the state of equipment, which provides enormous opportunities (PWC, 2014).

In this thesis we propose an innovative service logistics network design for each service region, from which we expect that it can realize extremely short solution times to service requests by exploiting the trend of real-time data becoming increasingly available. In this new design, there is a local warehouse and there are service engineers that carry no car stock. We assume that, upon a failure of a system, a perfect remote diagnosis, using real-time data, can be executed. Subsequently, a service engineer is dispatched to the failed system and, independently from the service engineer, a spare part is delivered from the local warehouse to the failed system by a fast transportation mode (e.g., a parcel carrier). Whenever a service engineer is dispatched to the failed system, it may leave a significant part of the service region without coverage. It could therefore be beneficial to reposition idle service engineers to maintain a proper coverage level in anticipation of future demand, after having dispatched a service engineer to a failed system. Furthermore, in practice, penalty costs for not being able to repair a failed system before the solution time target is exceeded, are significantly higher than the cost of repositioning idle service engineers. Consequently, dispatching and

repositioning idle service engineers in a smart way could lead to significant savings in operating costs in this innovative service logistics network design. This leads to the overarching objective of this thesis, which is to develop scalable heuristics that perform well and which are focused on both pro-actively repositioning of service engineers and deciding which service engineer to dispatch to service requests in a cost-efficient way.

Maintenance and service logistics is a topic widely studied in the literature. One of the important areas in maintenance and service logistics that has been studied extensively, is the area of spare parts management, where the focus mainly lies on (multi-item) spare parts optimization models. However, much lesser attention has been devoted to the planning or management of service engineers that are required to install or repair these parts, and none attention has been devoted to the planning of these service engineers with an explicit focus on realizing short solution times. Interestingly enough, the problem of planning the service engineers to realize short solution times, in isolation, is not unique to service logistics, but also appears in the vast literature of Dynamic Ambulance Management (DAM), where dispatching and repositioning decisions also have to be made in real-time. Namely, in life-threatening emergencies, ambulances should be dispatched to and reach these emergencies within extremely short response times. Most research in DAM focuses either on how to pro-actively reposition idle ambulances such that the coverage is maximized or on dynamic dispatching methods, that take into account the current state of the system in the dispatch decision. Hence, despite the aforementioned relation between them, dynamic dispatch and reposition decisions have predominantly been studied in isolation in DAM literature. To that end, we are the first to jointly consider dynamic dispatch and reposition decisions and we apply it in a service logistics network.

We formulate the dynamic dispatch and reposition problem as a Markov Decision Process (MDP) and solve this problem to optimality for a small, artificial service logistics network. We then propose scalable dynamic and static heuristics for both the dispatch and reposition sub-problem, based on the numerical investigation of the optimal policy. Hence, although the MDP solves both the dispatch and reposition problem in an integrated way, we decompose the problem into two sub-problems and design a heuristic independently for both the dispatching and repositioning sub-problems. This is also common in practice, where managers at service organizations are faced with two main problems in real-time: a dispatching problem and reposition problem. The developed dispatching (repositioning) heuristics are generic in the sense that they can be combined with any repositioning (dispatching) heuristic. Our static heuristics are characterized by rules of thumbs that are determined a-priori which are then always followed, regardless of the current state of the network. By contrast, our dynamic heuristics are characterized by maximizing a goal function that takes into account information about the current state of the network. Our proposed dynamic dispatch heuristic, based on the minimum weighted bipartite matching problem, is the first dynamic heuristic that assigns a fleet of service engineers to failed capital goods that takes into account real-time data about the state of equipment and the current position of each service engineer, whereas the static dispatching heuristic is the widely adopted ‘closest-idle first’-heuristic. Both our static and dynamic reposition heuristic are based on

the maximum expected covering location problem and they take into account both penalty costs and demand information of the capital goods. Current models, both in literature and in practice, limit themselves by imposing the constraint that once a decision has been made (either to dispatch or to reposition) the service engineer becomes eligible for a new decision once it has completed its service or has arrived at its final location. We analyze the benefit of relaxing this assumption by analyzing the allowance of reallocation in the policy, i.e. being flexible in deviating from previous dispatch and reposition decisions. Combining the option of whether or not reallocating with two options each for both the dispatching and repositioning sub-problem, leads to eight proposed heuristic policies in total.

We compare the performance of our proposed heuristics against the optimal policy in a small network in a small test bed and against a myopic policy, the SDSR heuristic (static dispatching heuristic, static repositioning heuristic, no reallocation), that is currently used in practice across a large test bed of industrial size. In the small test bed, we show that the average and the maximum optimality gap over all examined symmetric problem instances of the DDDR-R heuristic (dynamic dispatching heuristic, dynamic repositioning heuristic, reallocation), our most advanced and best-performing heuristic, are 4.6% and 10.4%, respectively. This is a clear improvement compared to the myopic SDSR heuristic, which has optimality gaps of 99.0% and 322.6%, respectively. However, in a rather pessimistic test bed, we find that the same DDDR-R heuristic performs worse with optimality gaps of 37.8% and 73.9%, respectively. Nevertheless, in the same test bed we observe that this was still a clear improvement compared to the myopic SDSR heuristic (optimality gaps of 99.9% and 224.5%, respectively). As the overarching objective of this thesis is to develop scalable heuristics that perform well in practice, we conduct a large test bed with networks of industrial size. In this large test bed, we show that huge savings can be obtained by either employing a dynamic dispatching policy or allowing for reallocation in the policy. The combination of both using the dynamic dispatching policy and allowing for reallocation, where we observe savings of up to 61.9%, results in the highest savings in the real-life service logistics networks.

Finally, we quantify the benefit of individually using either a dynamic dispatching heuristic, a dynamic repositioning heuristic or allowing reallocation in the policy. We show that savings of close to 50% can be attained by letting each service engineer be eligible for dispatch and reposition decisions, regardless of whether they are on their way to their destination or have already reached their destination. This quantification, which is currently lacking in the literature, shows that it is very beneficial from a cost-perspective to relax the limitation of no reallocation, regardless of the policy used. This analysis of individual benefits also shows that using the proposed dynamic dispatching heuristic, instead of the widely adopted ‘closest-idle first’-heuristic, results in savings of 27.7%

Preface

This thesis marks the end of not only my graduation project conducted at CQM in collaboration with Eindhoven University of Technology, but also of the five-year student period that I thoroughly enjoyed. I would like to take a moment to thank everyone who supported me along this journey.

First and foremost, I am deeply grateful to Geert-Jan van Houtum, my first supervisor, for your excellent guidance the past two years. Without your critical view and invaluable suggestions, this thesis would not have materialized. Your passion for doing research made me enthusiastic for pursuing PhD research, in which I hope we can continue our pleasant collaboration. I would like to thank Tom van Woensel, my second supervisor, for your useful feedback and valuable remarks on this thesis. Additionally, I would like to thank Joachim Arts for your willingness to complete my thesis assessment committee.

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CHAPTER 1

Introduction

Capital goods - such as MRI scanners, industrial printers or ATMs - are expensive, technologically complex systems that are used in the primary processes of their users. Therefore, their uptime is of utmost importance; each minute of unplanned downtime may be costly, risky (in case of medical equipment), or both. As a result, the total unplanned downtime should be minimized.

Many capital goods are being maintained by means of a service logistics network, which is owned and managed by a service organization. Such a network typically consists of a single central warehouse and many service regions (mostly determined by geographical borders) in which the capital goods are installed (see Basten and Van Houtum (2014)). Generally, spare parts are kept on stock both in the central warehouse and in the vehicles of the service engineers that operate in service regions. Upon failure of a capital good, a service engineer is dispatched to this failed capital good if the problem cannot be solved remotely. A failure is often caused by a failed part which can then be replaced immediately by a new part if the dispatched service engineer has this part in its car stock. Otherwise a (costly) second visit is needed, which usually occurs the next day. The spare part that is required is then delivered from the central warehouse during the night.

Service organizations invest heavily in maintenance and services to minimize the amount of unplanned downtime. In a recent survey, the Dutch Organization for Maintenance (Nederlandse Vereniging voor Doelmatig Onderhoud) reported that services and spare parts constituted, with a total amount of 30-35 billion euro, 4% of the gross domestic product of the Netherlands¹. In the same survey, it is estimated that the maintenance and service logistics industry employs 280.000-300.000 service engineers.

According to a recent survey among executives, one of the two top challenges for service organizations is the increasing demand from customers for better service (Pinder Jr, 2016). In practice, this means that although customers are currently satisfied when failures are solved within a day, in the future customers

¹NVDO. (2017, January 22). Maintenance en Service Logistiek slaan handen in één. Retrieved from: <http://www.nvdo.nl/nieuws/maintenance-en-service-logistiek-slaan-handen-ineen-3418/>

demand solution times (i.e. the time between the service call and the completion of solving the failure) of 1-2 hours or even lower in case of critical medical systems (e.g., IGT or iXR systems of Philips Healthcare that are used during surgeries).

Recent developments of communication networks and easy-to-integrate sensors allow service organizations to collect real-time data about the state of equipment, which provides enormous opportunities (PWC, 2014). Especially, executing a perfect remote diagnosis upon failure of a capital good before a service engineer is dispatched, will be a game changer in having the right spare part at the failed capital good in a timely fashion. This diagnosis will namely indicate whether a particular spare part is needed and, if so, which part, thereby enabling short solution times.

In this research, we want to analyze an innovative network design for a service region, from which we expect that it can realize extremely short solution times by exploiting real-time data. Figure 1.1 shows the conceptual model of this network design. In this design, there is a local warehouse and there are service engineers that carry no car stock. We assume that, upon a failure of a system, a perfect remote diagnosis can be executed. Subsequently, two procedures are initiated; i) a service engineer is dispatched to the failed system; ii) the spare part is delivered from the local warehouse to the failed system by a fast transportation mode (e.g., a parcel carrier). In the second procedure, we exploit the future possibility of remote diagnosis such that the correct spare part is sent. It is important to note that whenever a service engineer is dispatched to the failed system, it may leave a significant part of the service region without coverage. It could therefore be beneficial to reposition idle service engineers to maintain a proper coverage level in anticipation of future demand, after having dispatched a service engineer to a failed system. Furthermore, in practice, penalty costs for not being able to repair a failed system before the solution time target is exceeded, are significantly higher than the cost of repositioning idle service engineers. Consequently, repositioning idle service engineers in a smart way could lead to significant savings in operating costs. When customers demand solution times that are extremely low, service engineers have to be dispatched quickly upon a failure of system. This can only be achieved when service engineers are predominantly idle, i.e. when their utilization is low. As a result, the importance of repositioning idle service engineers in a smart way, will - in light of the trend of decreasing solution times - only increase.

Managers of service organizations are faced with three decisions (not to be confused with the two procedures that are initiated upon a failure of a system) in the design and control of such an innovative network:

1. How many service engineers are needed? (tactical)
2. How many and which spare parts should be stored in the local warehouse? (tactical)
3. How should service engineers be dispatched in response to or reposition in anticipation of a failure? (operational)

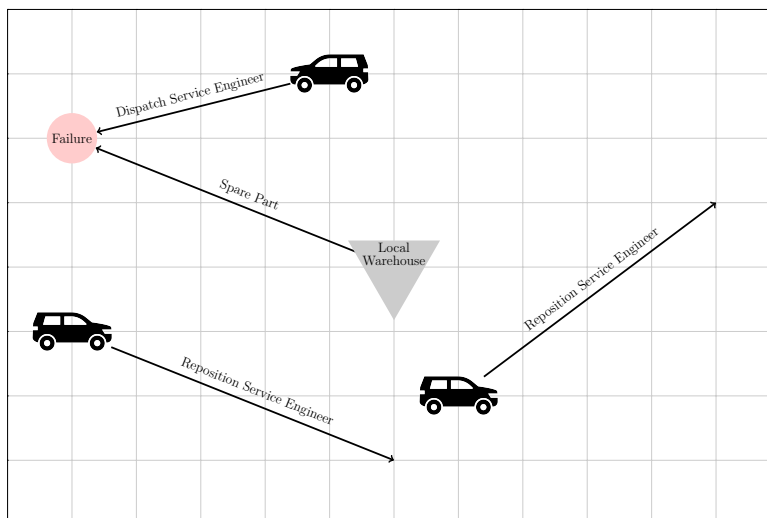


Figure 1.1: Illustration of network design

In practice, service organizations have contracts with their customers that prescribe the service that they should attain in terms of a certain fraction of failed systems that should be repaired within a certain time window (e.g., 95% of all failures should be repaired within 3 hours after the service call). Hence, we want to design and control this network such that this service measure - specifically a very low threshold - is attained in a cost-efficient way. In this thesis, we focus on the operational decision that has to be made, i.e. decision 3, and leave the other two decisions for future research. The reason for this is threefold. First, we are the first to address this innovative network and we intend to start from the operational decisions before we move on to the tactical decisions (i.e. a bottom-up approach). Second, despite the practical relevance and the aforementioned relation between them, dynamic dispatch and reposition decisions have only been studied in isolation in literature (as we will see in our literature review). To that end, by answering question 3 in this thesis, we are the first to jointly consider dynamic dispatch and reposition decisions in a service logistics network, thereby having a clear contribution to the related literature. Third, as we will see in the remainder of this thesis, the complexity of question 3 is already sufficiently high to devote this whole thesis research to it.

The overarching objective of this thesis is therefore to present a tractable optimization model that assists decision makers in answering question 3. More specifically, we intend to come up with scalable heuristics that perform well and which are focused on both pro-actively repositioning of service engineers and deciding which service engineer to dispatch to service requests in a cost-efficient way. Despite the common usage of scalability when addressing heuristics, the issue whether a heuristic can be deemed as scalable itself differs from research to research depending on the objective of the heuristic. In this thesis we adopt the same meaning of scalability of a heuristic as Caseau and Laburthe (1999), where a heuristic is scalable if it can be used to make good decisions in a suitable time horizon in problems of real-life size. Since we address

a real-time problem, the length of a time horizon is suitable when decisions can be made instantaneously, meaning that the time complexity of our proposed heuristics should be low.

The main contribution of this thesis is fourfold:

- We are the first to jointly address the real-time dispatch and reposition problem of service engineers in a service logistics network to realize short solution times. We formulate the real-time service engineer dispatch and reposition problem, which we solve to optimality for small instances. By means of a numerical investigation, we are the first to show that the optimal policy for the dispatch and reposition problem of service engineers exhibits certain behavior with respect to three aspects, i.e. location strategy for idle service engineers, dispatching strategy of service engineers that takes into account the state of the system, and reallocation of service engineers.
- We propose scalable dynamic and static heuristics for both the dispatch and reposition sub-problem, based on the numerical investigation of the optimal policy. Our static heuristics are characterized by rules of thumbs that are determined a-priori which are then always followed, regardless of the current state of the network. By contrast, our dynamic heuristics are characterized by maximizing a goal function that takes into account information about the current state of the network. Our proposed dynamic dispatch heuristic, based on the minimum weighted bipartite matching problem, is the first dynamic heuristic that assigns a fleet of service engineers to failed capital goods that takes into account real-time data about the state of equipment and the current position of each service engineer. Both our static and dynamic reposition heuristic are based on the maximum expected covering location problem and they take into account both penalty costs and demand information of the capital goods, where the dynamic variant maximizes the expected weighted coverage of future service requests.
- We compare our proposed heuristic dispatch and reposition policies on a wide range of both small and large problem instances. In a small test bed, we show that our most advanced heuristic performs excellent under specific circumstances, but strictly outperforms all other heuristics across all instances. To show the practical value of our proposed heuristics, we conducted extensive numerical experiments with service logistics networks of industrial size. In these numerical experiments we show that our most advanced heuristic greatly outperforms (up to 61.9% savings) the myopic policy that is common in current practice.
- We quantify the benefit of individually using either a dynamic dispatching heuristic, a dynamic repositioning heuristic or allowing reallocation in the policy. We show that savings of close to 50 percent can be attained by letting each service engineer be eligible for dispatch and reposition decisions, regardless of whether they are on their way to their destination or have already reached their destination. This quantification, which is currently lacking in the literature, shows that it is very beneficial from a cost-perspective to relax the limitation of no reallocation, regardless of the policy used. This analysis

of individual benefits also shows that using the proposed dynamic dispatching heuristic, instead of the widely adopted ‘closest-idle first’-policy heuristic, results in savings of 27.7%.

The remainder of this thesis is structured as follows. In Chapter 2, we provide a review of related literature and we position the contribution of this work with respect to existing literature. In Chapter 3, we give a formal problem definition. In Chapter 4, we translate the formal problem definition into a Markov Decision Process. In Chapter 5, we present insights into the optimal policy that we use in designing eight scalable heuristics in Chapter 6. In Chapter 7, we present a computational study to evaluate the performance of our scalable heuristics in both a test bed for small instances and a test bed that is of industrial size. Finally, we end with our conclusion and discussion in Chapter 8.

CHAPTER 2

Literature review

Maintenance and service logistics is a topic widely studied in the literature. One of the important areas in maintenance and service logistics that has been studied extensively, is the area of spare parts management (we refer the reader to Basten and Van Houtum (2014) and Van Houtum and Kranenburg (2015) for an excellent overview of spare parts management), where the focus mainly lies on (multi-item) spare parts optimization models. However, much lesser attention has been devoted to the planning or management of service engineers that are required to install or repair these parts. In this research, we study the real-time management of service engineers in service logistics networks.

We structure our literature review according to the solution time target that needs to be attained. We do so since, as we see in the remainder of this chapter, the solution time target determines in which class of problems the management of service engineers falls and hence also which analysis techniques are applicable. The main focus lies in the range of short solution times, however in order to provide a complete overview, we shortly discuss related literature when solution time targets are high and medium, respectively. We conclude this chapter by providing an extensive overview of the related literature when solution time targets are low. Here, we position our work and we also discuss why particularly this stream of literature relates to our problem.

2.1 High solution times

At first glance, the main stream of literature that seems to be related to this work is the area of dynamic vehicle routing problems. When solution time targets are high, management of service engineers mainly consist of routing them dynamically (i.e. there is an explicit routing dimension inherent to the decisions that are made) to known and upcoming requests throughout the day, which is a typical Dynamic Vehicle Routing Problem (DVRP) (Laporte, 1992). We refer to Pillac et al. (2013) for an overview of the available

techniques (e.g., Approximate Dynamic Programming (ADP), meta-heuristics) for DVRPs.

2.2 Medium solution times

When solution time targets are of medium level, management of service engineers should not only consist of routing decisions but should also anticipate future demand with more caution. That is, the decisions should reflect that in some regions service request could arrive in the near future by diverted routes from one service request to another. Such a path would then anticipate a service request in between a route from one known service request to another known service request, thereby increasing the chance of adhering to the solution time target if the anticipated service request realizes. This problem relates to the new class of Anticipatory Routing Problems (ARPs), which also falls under broad category dynamic and stochastic routing problems. In ARPs, vehicles are routed dynamically to known demand in anticipation of future demand. Thomas and White III (2004), Thomas (2007), Ulmer et al. (2015) and Ulmer et al. (2017) all studied ARPs and developed algorithms based on Markov Decision Processes (MDP) to route a single vehicle. The research of Ichoua et al. (2006) extended the problem to a multi-vehicle setting but they do not exploit real-time information.

2.3 Short solution times

As stressed out in the introduction, we study the management of service engineers in service logistics networks to realize short solution times such that this challenge for service organizations can be coped with in the near future. To the best of the our knowledge, there is no literature that explicitly focuses on this subject. Moreover, real-time management of service engineers to realize short solution times, in contrast to high or medium solution time target, is dominated by dispatching and repositioning decisions, instead of (anticipatory) routing decisions. This makes the problem inherently different from the aforementioned types of problems. Consequently, even though the literature on dynamic and stochastic routing problems seems applicable to our problem, we will not use results from, nor will we contribute to these streams. Hence, we resort ourselves to a complete different stream of literature where the focus lies also on dispatching and repositioning decisions, albeit in a different application domain.

Interestingly enough, the problem of planning the service engineers to realize short solution times, in isolation, is not unique to service logistics, but also appears in the vast literature of ambulances and fire-fighters management. For instance, in life-threatening emergencies, ambulances should be dispatched to and reach these emergencies within extremely short response times. Since we want to realize short solution times, the real-time management of service engineers in our network show similarities with the real-time management

of emergency providers.

In particular, the concept of Dynamic Ambulance Management (DAM), where the expected fraction of late-arrivals of ambulances is minimized, has gained momentum in recent years. See Maxwell et al. (2014) for an overview of the widely used techniques for DAM (e.g., MDP theory), where the main concern is the lack of scalability to large-scale systems due to the curse of dimensionality (Powell, 2007). To overcome this, some researches have focused on developing DAM heuristics based on Approximate Dynamic Programming (ADP) (e.g., Maxwell et al. (2010) and Schmid (2012)), while Naoum-Sawaya and Elhedhli (2013) formulated DAM heuristics based on two-stage Stochastic Programming, and Alanis et al. (2013) formulated a DAM heuristic based on a two-dimensional Markov chain model. More recently, Van Barneveld et al. (2016), Van Barneveld et al. (2017), Jagtenberg et al. (2015) and Jagtenberg et al. (2016) have considered DAM-policies in real-life EMS networks, where they developed real-time heuristics that outperformed myopic policies.

The vast majority of the papers on DAM focuses on how to pro-actively reposition idle vehicles such that the coverage is maximized. This ensures that future incidents get a larger likelihood of being reached in time, thereby increasing the total expected fraction of incidents that can be reached within the time threshold. Jagtenberg et al. (2015) show that pro-actively repositioning significantly outperforms static policies in which idle ambulances always return to a base station in terms of minimizing late-arrivals. With regard to the actual dispatching (i.e. deciding which ambulance to dispatch to incidents), most articles assume a static dispatch rule: whenever an incident occurs they use the ‘closest-idle first’-policy. Such a ‘closest-idle first’-policy is due to both regulatory and ethical reasons most common in practice (Schmid, 2012), but, as the research of Jagtenberg et al. (2016) shows, at the same time far from optimal if the goal is to minimize late-arrivals. Intuition behind this sub-optimality lies in the notion of coverage. Always sending the closest-idle vehicle could lead to a, from a system perspective, sub-optimal coverage, thereby decreasing the total expected fraction of incidents that can be reached within the time threshold.

Only few papers in the DAM literature focus on dynamic dispatching methods, which is also the focus of our research. The exceptions are Jagtenberg et al. (2016), Naoum-Sawaya and Elhedhli (2013) and Schmid (2012), where Naoum-Sawaya and Elhedhli (2013) and Schmid (2012) are the only ones that jointly address dynamic dispatching and dynamic repositioning policies. Dynamic dispatching methods, in contrast to static dispatching methods such as the ‘closest-idle first’-policy, take into account the current state of the system in the dispatch decision. Hence, dynamic dispatching methods do not rely on a-priori decision rules that are always taken regardless of the state of the system, as is the case with their static counterpart.

Jagtenberg et al. (2016) consider dynamic dispatching of ambulances to requests, where the objective is to minimize late-arrivals (i.e. arrivals that exceed a certain time threshold). The problem is formulated as an MDP and due to the restriction that ambulances always have to return to a static base station (i.e. they consider a static reposition policy), their state space remains tractable. Hence, using value iteration,

the authors are able to compute the optimal policy. For larger instances, they propose a fast and efficient heuristic based on the maximum expected covering location problem (Daskin, 1983) which performs close to the optimal solution from the MDP. In this research, we also use structural results from the maximum expected covering location problem to design an efficient heuristic, albeit in a different way. There are two differences between their problem and our problem. First, idle ambulances always return to their static base station, which is known to be suboptimal (see Jagtenberg et al. (2015)), whereas in our problem, service engineers can immediately serve other service calls without returning to their base station. Second, similar to the research of Schmid (2012), if there are idle ambulances and an incident occurs, an ambulance has to be dispatched, which is not the case in our research.

Naoum-Sawaya and Elhedhli (2013) formulate a two-stage stochastic optimization model for both the redeployment and dispatching of ambulances that minimizes the number of re-locations over a planning horizon while maintaining an acceptable service level. Their approach falls in the class of periodic re-optimization methods (see Pillac et al. (2013)), as they solve the problem periodically for each planning horizon. In this approach, critical information is revealed over time, meaning that the complete instance is only known at the end of the planning horizon. As a consequence, the method only provides solutions for the current state which relies on currently available data, but do not guarantee that the solution will remain good once new data becomes available. In this thesis however, we intend to integrate stochastic knowledge about future states analytically such that we formally capture the stochastic nature of the problem. Furthermore, their modeling approach relies on the assumption that scenarios are known and that they are of medium size, such that optimization can take place instantaneously. By contrast, in service logistics of real-life size, this assumption will probably not hold, which makes this modeling approach not suitable for our problem.

Schmid (2012) considers both the dispatching of ambulances to request sites and the repositioning of ambulances before and after they have served a request. They propose a dynamic programming model and solve this model using ADP due to the intractability of it. There are two differences between their study and our problem. First, if there are idle ambulances and an incident occurs, an ambulance has to be dispatched. In our problem, we can choose to postpone a service call. Second, after an incident, an ambulance always returns to the hospital before becoming idle again whereas in our problem a service engineer is immediately available after the visit.

Even though the same decisions (i.e. dispatch and reposition decisions) have to be made in our research and DAM research, there are two differences with our research that all aforementioned DAM studies have in common. First, in DAM literature, all models limit themselves by imposing the constraint that once a decision has been made (either to dispatch or to reposition) the vehicle becomes eligible for a new decision once it has completed its service or has arrived at its final location. In other words, reallocation is not allowed. We hypothesize however that it could be beneficial to reallocate (e.g., when a service request arrives on or next to a already determined route of a service engineer) and we therefore include and analyze this

possibility in our research. Second, whereas the performance in DAM studies is predominantly formulated in response times (actual time between arrival of emergency and arrival at the scene) for obvious reasons, the performance in our research is formulated in monetary terms. In the former, being to late at a scene can result in life-threatening situations (or worse, casualties), whereas in the latter a penalty cost will be incurred, which is a fundamental difference that we need to include in our research.

As stressed out in the introduction, we intend to come up with scalable heuristics that perform well in practice and are focused on both pro-actively repositioning of service engineers and deciding which service engineer to dispatch to failures. Here, the goal is to minimize the late-arrivals after a certain threshold such that a certain performance measure is attained. More specifically, we intend to integrate the models of Jagtenberg et al. (2015), Jagtenberg et al. (2016), Schmid (2012), and extend the models in light of the differences, where we especially incorporate the possibility of reallocation. Our goal is to use the same techniques to formulate the problem, namely techniques from Markov decision theory. Subsequently, we use exact analysis (e.g., value iteration) in case of small instances and in order to understand the optimal policy, and then develop scalable heuristics for larger instances of industrial size. The quality of these scalable heuristics can then be compared to static policies that are mostly used in practice using simulation.

Model description

In this chapter, we introduce the real-time service engineer dispatch and reposition problem. We first formulate the dispatch and reposition problem in mathematical terms and describe the problem in more detail. We then conclude this chapter by both summarizing and justifying the assumptions we have made in modelling the dispatch and reposition problem.

3.1 Dispatch and reposition problem

We model the service region of interest as a graph, with finite node set \mathcal{N} . For notational convenience, the nodes are assumed to be numbered $n = 1, \dots, |\mathcal{N}|$. There are two types of nodes: demand nodes and non-demand nodes. The former are nodes where capital goods are installed and hence where demand can occur. Additionally, service engineers can wait at these nodes in anticipation of future demand or travel via these nodes to other nodes. The latter are nodes in the network where service engineers can only reside in anticipation of future demand or nodes that lie on their route when they are dispatched to failures. These disjoint sets are denoted by \mathcal{N}^d and $\mathcal{N}^w = \mathcal{N} \setminus \mathcal{N}^d$, respectively. Hence, the sole purpose of non-demand nodes $i \in \mathcal{N}^w$ is waiting or routing, whereas demand nodes $j \in \mathcal{N}^d$ have the additional property that demand can occur at these nodes. For simplicity, we number the nodes in such a way that the first $|\mathcal{N}^d|$ nodes in the numbering represent the demand nodes, i.e.; $\mathcal{N}^d = \{1, 2, \dots, |\mathcal{N}^d|\}$, $\mathcal{N}^w = \{|\mathcal{N}^d| + 1, \dots, |\mathcal{N}|\}$. Furthermore, let $\mathcal{N}_i \subseteq \mathcal{N}$ be the set of neighboring nodes of node $i \in \mathcal{N}$. The total number of identical service engineers in this region is denoted by N and we assume that service engineers are indistinguishable.

We assume that the length of each edge equals 1, so it takes one time step to traverse an edge. Consequently, our graph is a unit distance graph, which is a special case of a graph where all edges have length 1. Hence, time is discretized in time steps of Δt , which enables us to keep the problem size and its analysis tractable (as we will see in the next chapter). These discrete points in time also mark the decision epochs at which

all information about the events that occurred in the preceding time step becomes available to the decision maker. As a consequence, it takes a service engineer Δt time (e.g., 20 minutes) to cross an edge. In practice, the graph should be constructed in such a way that Δt is sufficiently small enough to model service engineer movements. To model more realistic situations, one could decrease Δt , but then the graph should be scaled accordingly by adding more nodes and edges. For $\Delta t \rightarrow 0$, this model becomes continuous in both time and space.

At each node $i \in \mathcal{N}^d$, we assume that exactly one capital good is installed. The capital good is composed of critical and non-critical components. When a critical component of a machine fails, the whole machine goes down, while a machine can continue its functioning upon the failure of a non-critical component. We limit ourselves to the failures of critical components, since these failures have a high impact in terms of downtime. Furthermore, the components under consideration that fail are only repaired by replacement, meaning that we limit ourselves to corrective maintenance. Such a failed part will be replaced by a new part, for which we here assume that it has arrived at or before the service engineer arrives (this relates to the spare parts planning sub-problem).

Upon the failure of a component, a service request arrives at the start of the next decision epoch at the central decision maker. In practice, this is often either the original equipment manufacturer or a service organization that is responsible for the maintenance function. The decision maker now has to choose how to dispatch and reposition service engineers such that this service request is fulfilled in the near future. Note that he may also choose to postpone service requests. That is, not immediately deciding to dispatch a service engineer to this node or to start the repair. When a service engineer arrives or already resides at the node where the failed capital good is installed, the repair can start after the central decision maker decides to perform a repair at that particular node, which takes Δt time units by assumption. See Figure 3.1 for a graphical representation of this repositioning and dispatching process. Here, a capital good fails during $[\Delta t, 2\Delta t)$, for which the service request arrives at the central decision maker at $t = 2\Delta t$. The central decision maker now decides to reposition a service engineer in the direction of the failed capital good. At $t = 4\Delta t$, a service engineer arrives at the failed capital good, after which the decision maker immediately decides to repair the capital good. This repair is finished at $t = 5\Delta t$, after which the service engineer is again repositioned.

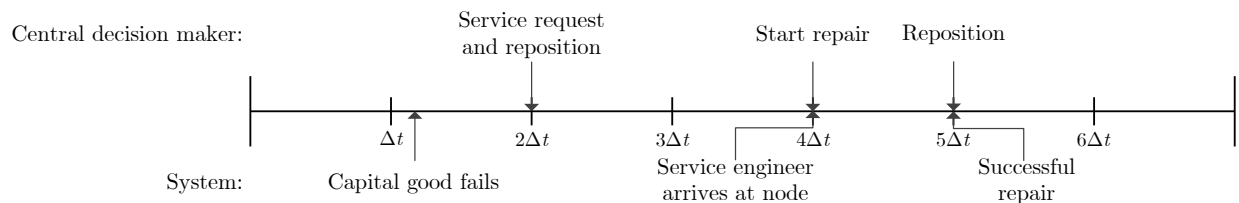


Figure 3.1: Order of events

The failures of the components at each node $i \in \mathcal{N}^d$, occur according to a Poisson process (i.e. their lifetimes are exponentially distributed random variables) with rate $\lambda_i(\Delta t)$. Although $\lambda_i(\Delta t)$ depends on the chosen time step size Δt , we will omit this dependence in the remainder of this thesis by simply choosing, without loss of generality, $\Delta t = 1$. Let us define $p_i^0(\Delta t)$ and $p_i^1(\Delta t)$ as the probability that the capital good at node $i \in \mathcal{N}^d$ has failed and not failed, respectively, during discrete time step Δt . Similar to the parameter of the Poisson process, these probabilities depend on the chosen time step size Δt , but we again select $\Delta t = 1$ and omit this dependence in the remainder of this thesis. Since demand at node $i \in \mathcal{N}^d$ occurs according to a Poisson process with a constant rate λ_i , we have: :

$$p_i^0 = P(X_i < 1) = 1 - e^{-\lambda_i}. \quad (3.1)$$

$$p_i^1 = 1 - P(X_i < 1) = e^{-\lambda_i}, \quad (3.2)$$

where X_i represents the life time distribution of the critical component in the capital good at demand node i , which is an exponentially distributed random variable. Our objective is, first of all, formulated in terms of the solution times to failures: The time between the arrival of the service request and the moment a service engineer completes the repair of the failure. In service logistics networks, service contracts postulate a solution time threshold T for solution times (which is equal to the time between the moment the service request becomes known to the decision maker and the moment the repair has been completed) that should be achieved for a certain fraction of service requests (e.g., service requests should be solved within 100 minutes). Otherwise, a cost penalty, denoted by $\alpha_i (< \infty)$ for node $i \in \mathcal{N}^d$, has to be paid by the service organization to their customer. Therefore, we look for a dynamic dispatch and reposition policy that minimizes the fraction of service requests for which the solution time is larger than T .

Second, in practice, service organizations also often want to serve the delayed service requests as fast as possible even though the solution time is larger than T . This is mostly because a linear penalty cost, denoted by $\beta_i (< \infty)$ for node $i \in \mathcal{N}^d$, is agreed upon for delayed service requests for the time period between the time threshold T and the point in time that the capital good is repaired.

Finally, service organizations also incur costs that are related to traveling of their service engineers, we therefore assign a weight $\gamma (< \infty)$ to the number of edges that are traveled by the service engineers, representing the traveling costs (e.g., gasoline, insurance). Hence, as we will see in the next chapter where we present the mathematical formulation of the problem, we formulate the objective such that all relevant costs are taken into account. Interviews with our industrial partner, a large manufacturer of industrial printers, confirmed that this cost structure indeed captures all relevant costs that are common in practice. As a performance criterion, we are interested in the long-run average cost per time unit.

3.2 Overview of assumptions

We summarize and discuss the main assumptions introduced in the previous section:

1. *Service engineers are indistinguishable.* This assumption is made since we are interested in dynamic dispatching and reposition policies from a system perspective, meaning that we centrally organize the fleet of service engineers. To solely focus on the configuration of the whole fleet, we assume that each service engineer can be treated equally. In practice, this assumption is justified if service engineers have the same background and training which results in that they have developed the same set of skills.
2. *The length of each edge equals 1, which takes one time step Δt to traverse.* For $\Delta t \rightarrow 0$, this model not only becomes continuous in both time and space but also more accurate, which results in a realistic model. For larger values of Δt , the model becomes less accurate in the sense that the model does not differentiate between events that occur at the start and end of time period $[t, t + \Delta t)$.
3. *Each node $i \in \mathcal{N}^d$ has exactly one installed capital good.* We use this assumption to keep the state space tractable in our model formulation, which we will see in the next chapter. From a practical point of view, if multiple capital goods are installed at a location, then one could model this situation by a single node for each of these goods. Consequently, this means that even though the distance between these goods are zero from a practical point of view, they are separated Δt from each other from a modeling perspective. When Δt becomes small, this difference not only becomes negligible but also allows us to differentiate in repairing individual capital goods at a single location which could lead to a more flexible policy. Furthermore, interviews with our industrial partner confirmed that, due to high investment costs of these capital goods, most locations have only one installed capital good, with a few locations having more than one installed capital good.
4. *Repair times are deterministic and take Δt time units.* The assumption of deterministic repair times is justified since in our model, it is known beforehand which spare part needs to be repaired. Hence, service engineers are prepared for the repair which means that we can consider the variability in the duration of the repair as negligible. Furthermore, it allows us to formulate the problem with a tractable mathematical model, which we will see in the next chapter. In the next chapter, we also show that our model can easily be extended to incorporate deterministic repair times that are an integral multiple of Δt , resulting in a more realistic model.
5. *Service requests (demand) at each node arrive according to a Poisson process with constant rate.* This is a common assumption in literature and allows a tractable analysis as we will see in the next chapter. Moreover, the assumption is often justified in practice (cf. Caglar et al. (2004); Sherbrooke (2006); Graves (1985)). Additionally, it is reasonable to assume constant failure rates since in practice, long

down-times of capital goods are not allowed.

Despite the benefit of being able to formulate a tractable model due to the key assumption in our model, i.e. both time and space are discretized in steps of length Δt , it considerably simplifies the problem at hand. Consequently, the results of our tractable model do not hold directly in practice, but should be looked at while taking into account the limitations of this key assumption. We reflect on these limitations in Chapter 8.

Markov decision process formulation

In this chapter, we model the problem that has been discussed in the previous chapter as a Markov Decision Process (MDP). We start by formulating the state space, which remains tractable due to our choice to discretize both space and time. We then describe the action space, which is focused on both the configuration of the fleet of service engineers and the repairs. Subsequently, the transition probabilities are discussed. The MDP formulation is then finalized by formulating the direct expected cost, which takes into account costs for both reaching a failure too late, i.e. exceeding the solution time threshold, and for the total travel distance of the service engineers. We conclude this chapter by providing an illustrative example that shows the underlying dynamics of our MDP.

4.1 State space

For each node $i \in \mathcal{N}^d$, the tuple $s_i = (y_i, \sigma_i)$, represents the local state of node i , where $y_i \in \{0, 1, \dots, N\}$ represents the number of service engineers that are currently residing at node i , and $\sigma_i \in \{0, 1, \dots, \hat{T}\}$ denotes the state of the capital good at node i . To be more precise, $\sigma_i = 0$ indicates that the capital good is up and running, whereas $\sigma_i \in \{1, \dots, \hat{T}\}$ means that the capital good has failed for σ_i time units, for each node $i \in \mathcal{N}^d$. Thus, by setting $\hat{T} = \lfloor \frac{T}{\Delta t} \rfloor + 1$, $\sigma_i = \hat{T}$ means that the capital good has failed for longer than solution time threshold T . Consequently, in light of our goal to minimize the fraction of service requests that exceed solution time threshold T , we only need to capture information about the state of the capital good until $\sigma_i = \hat{T}$. With regard to the non-demand nodes, for each node $i \in \mathcal{N}^w$ the local state $s_i = (y_i)$ only contains the number of service engineers that are currently residing at node i . In the remainder of this thesis, we use \mathbf{y} and $\mathbf{\Sigma}$ to denote the state vectors $(y_i)_{i \in \mathcal{N}}$ and $(\sigma_i)_{i \in \mathcal{N}^d}$, respectively. The state space of the entire system can be represented as:

$$\mathcal{S} = \{(s_i)_{i \in \mathcal{N}}\} = \{(s_1, s_2, \dots, s_{|\mathcal{N}|})\}$$

Throughout this thesis, we use $y_i(s)$ and $\sigma_j(s)$ to denote the number of service engineers at node $i \in \mathcal{N}$ and the state of the capital good at node $j \in \mathcal{N}^d$, respectively, when the state of the system is $s \in \mathcal{S}$. The size of the state space, $|\mathcal{S}|$, is restricted by imposing a logical constraint. As the total number of service engineers in our system is equal to $N < \infty$, we have that $\sum_{i \in \mathcal{N}} y_i(s) = N$ for each $s \in \mathcal{S}$. Hence, $|\mathcal{S}| = (\hat{T} + 1)^{|\mathcal{N}^d|} \cdot \binom{|\mathcal{N}| + N - 1}{|\mathcal{N}| - 1}$, where the latter term represents the number of ways of distributing N identical service engineers among $|\mathcal{N}|$ nodes such that each node can have 0 or more ($\leq N$) service engineers.

As a final note, our MDP formulation can easily be extended to incorporate deterministic repair times that are an integral multiple of Δt . Let r_i be the deterministic repair time that is required for the repair of the capital good located at demand node $i \in \mathcal{N}^d$. We then add for each demand node $i \in \mathcal{N}^d$ a new state parameter, denoted by z_i , to tuple s_i that represents how many time units ago a repair started, with $z_i \in \{0, 1, \dots, \hat{r}_i\}$. Then, by setting $\hat{r}_i = \frac{r_i}{\Delta t}$, we can model deterministic repair times that are an integral multiple of Δt and which can depend on the capital good located at demand node $i \in \mathcal{N}^d$. The action space and transition probabilities should also be changed accordingly, resulting in a higher dimensional MDP.

4.2 Action space

At each state $s \in \mathcal{S}$, a set of actions \mathcal{A}_s can be performed, which is a subset of the action space \mathcal{A} (i.e. $\mathcal{A} = \bigcup_{s \in \mathcal{S}} \mathcal{A}_s$). Such an action specifies for each node $n \in \mathcal{N}$ how many service engineers will be sent to each of its neighboring nodes, and for each node $m \in \mathcal{N}^d$ where a capital good has failed and at least one service engineer resides, whether a repair should be carried out or not.

The action space \mathcal{A}_s can be represented as:

$$\mathcal{A}_s = \{(A_i)_{i \in \mathcal{N}}, (R_i)_{i \in \mathcal{N}^d}\} = \{(A_1, A_2, \dots, A_{|\mathcal{N}|}), (R_1, R_2, \dots, R_{|\mathcal{N}^d|})\},$$

where tuple $A_i = (a_i^l)_{l \in \mathcal{N}_i}$, with $a_i^l \in \mathbb{N}_0$, represents the number of service engineers that are sent from node i to neighbouring node l and $R_i \in \{0, 1\}$ represents whether a repair is performed ($R_i = 1$) or not ($R_i = 0$) at node $i \in \mathcal{N}^d$. Analogously to the state space, the action space is thus a Cartesian product of local actions that apply to individual nodes in the graph. The actions are locally interacting (i.e. actions A_i and R_i solely influence x_i , $\{(x_j)_{j \in \mathcal{N}_i}\}$ or both) and the interaction network can be represented by the underlying graph. The action space \mathcal{A}_s is subject to the following restrictions:

$$R_i \in \{0, 1\} \quad \forall i \in \{j \in \mathcal{N}^d | y_j(s) \geq 1 \wedge \sigma_j(s) \neq 0\} \quad (4.1)$$

$$R_i = 0 \quad \forall i \in \{k \in \mathcal{N}^d | y_k(s) = 0 \vee \sigma_k(s) = 0\} \quad (4.2)$$

$$\sum_{l \in \mathcal{N}_i} a_i^l + R_i \leq y_i(s) \quad \forall i \in \mathcal{N}^d \quad (4.3)$$

$$\sum_{l \in \mathcal{N}_i} a_i^l \leq y_i(s) \quad \forall i \in \mathcal{N}^w \quad (4.4)$$

Equation (4.1) states that when at least one service engineer is at a node $i \in \mathcal{N}^d$ where a capital good has failed, we can take the decision to either repair ($R_i = 1$) or not ($R_i = 0$) (Equation (4.2)). For demand nodes, where there is no service engineer or the capital good is up and running or both, the default action to not repair the capital good (i.e. $R_i = 0$) is taken. Then, when the action to repair the capital good at node $i \in \mathcal{N}^d$, is taken, at least one service engineer has to reside at node i after the concurrent reposition actions are taken. This is expressed in Equation (4.3). Here, we assume that only one service engineer is needed to repair the failed capital good (the service engineer that remains at node i) and that a repair is non-preemptive. This is a reasonable assumption since in practice, repairs mostly require only one service engineer that completes the repair once started. Equation (4.4) states that the total number of service engineers that leave a certain node should be less than or equal to the number of service engineers that are currently residing at that node.

All other actions from \mathcal{A}_s that are not restricted by Equations (4.1)-(4.4) are feasible. This completely defines the allowed action space for each state. Hence, all service engineer movements are allowed, except that once the action to repair a capital good at a node is taken, at least one service engineer has to remain at this node to repair the capital good, which takes Δt time units.

4.3 Transition probabilities

Let $P_a(s, s')$ denote the probability that action a in state s at time t will lead to state s' at time $t + \Delta t$. This probability depends on the local transitions that occur at each node, i.e. the randomness in our model stems from the independent transitions that occur locally at each node $i \in \mathcal{N}$ during discrete time step Δt . More specifically, the state s' to which the system transitions after taking action a in state s is determined by three factors:

1. The random event that a capital good fails or not. This influences state vector Σ .
2. The decision to carry out a repair or not. This also influences state vector Σ .
3. The configuration actions of the service engineers. This impacts state vector \mathbf{y} through Equation (4.6).

Let $\hat{P}_a(s_i, s'_i)$ be the probability that non-demand node $i \in \mathcal{N}^w$ goes from local state s_i to local state s'_i due to action a . Analogously, let $\bar{P}_a(s_i, s'_i)$ be the probability that demand node $i \in \mathcal{N}^d$ goes from local state s_i to local state s'_i due to action a . Then we can define $P_a(s, s')$, which is the product of the local transition

probabilities, as follows:

$$P_a(s, s') = \prod_{i \in \mathcal{N}^w} \hat{P}_a(s_i, s'_i) \prod_{j \in \mathcal{N}^d} \bar{P}_a(s_j, s'_j) \quad (4.5)$$

With regard to the non-demand nodes, $\hat{P}_a(s_i, s'_i)$, can only take value 0 and 1, namely:

$$\hat{P}_a(s_i, s'_i) = \begin{cases} 1 & \text{if } y_i(s') = y_i(s) + \sum_{l \in \mathcal{N}_i} a_l^i - \sum_{l \in \mathcal{N}_i} a_l^l \\ 0 & \text{otherwise} \end{cases}$$

Logically, $\hat{P}_a(s_i, s'_i)$ takes value 1 if flow balance Equation (4.6) holds, otherwise, this local transition cannot occur. Just as with the non-demand nodes, for each of the local transitions from s_i to s'_i through action a at demand node $i \in \mathcal{N}^d$, it needs to hold that:

$$y_i(s') = y_i(s) + \sum_{l \in \mathcal{N}_i} a_l^i - \sum_{l \in \mathcal{N}_i} a_l^l \quad (4.6)$$

Then, $\bar{P}_a(s_i, s'_i)$ is defined as (in each of these cases Equation (4.6) also needs to hold):

$$\bar{P}_a(s_i, s'_i) = \begin{cases} p_i^1 & \text{if } [\sigma_i(s) = 0 \wedge \sigma_i(s') = 0] \\ p_i^0 & \text{if } [\sigma_i(s) = 0 \wedge \sigma_i(s') = 1] \\ 1 & \text{if } [\sigma_i(s) \neq 0 \wedge (R_i = 1 \wedge \sigma_i(s') = 0)] \vee \\ & [\sigma_i(s) \neq 0 \wedge (R_i = 0 \wedge \sigma_i(s') = \min\{\sigma_i(s) + 1, \hat{T}\})] \\ 0 & \text{otherwise} \end{cases}$$

In words, $\bar{P}_a(s_i, s'_i)$ takes value p_i^1 (see Equation (3.1) in Section 3.1), if the capital good at demand node i does not fail during discrete time step Δt . Next, the capital good at demand node i fails during discrete time step Δt with probability p_i^0 (see Equation (3.2) in Section 3.1), leading to a transition from $\sigma_i(s) = 0$ to $\sigma_i(s') = 1$. For each demand node i where a capital good has failed, it can either be repaired or not, depending on the action, leading to $\sigma_i(s') = 0$ or $\sigma_i(s') = \min\{\sigma_i(s) + 1, \hat{T}\}$, respectively, with certainty. Additionally, the flow balance of service engineers needs to hold (see Equation (4.6)). Other local transitions cannot occur.

4.4 Direct expected cost

Along with taking action a in state s , we incur a direct expected cost, denoted by $C_a(s)$, which consist of three parts; a cost for exceeding the solution time threshold T , a cost for each additional time unit by which

the solution time threshold T is exceeded, and a cost for the total distance traveled by the service engineers. $C_a(s)$ is then defined as:

$$C_a(s) = \sum_{i \in \mathcal{N}^d} \alpha_i \cdot \mathbb{1}_{[\sigma_i(s) = \hat{T} - 1 \wedge R_i = 0]} + \sum_{j \in \mathcal{N}^d} \beta_j \cdot \mathbb{1}_{[\sigma_j(s) = \hat{T} \wedge R_j = 0]} + \gamma \cdot \sum_{i \in \mathcal{N}} \sum_{l \in \mathcal{N}_i} a_i^l, \quad (4.7)$$

where $\mathbb{1}_{[x]}$ denotes the indicator function, which is 1 if x holds and 0 otherwise. This cost function assigns a weight to the number of service requests whose solution times exceed T , to the amount of remaining delayed service requests and to the amount of edges that are traveled by the service engineers. In practice, the latter represents costs related to traveling (e.g., gasoline, insurance). The magnitude of α , β and γ determines the emphasis that is put on maximizing the amount of service requests that are resolved within solution time T , minimizing the delay with which service requests are fulfilled, or minimizing the distance that is traveled by the service engineers.

4.5 Example

Figure 4.1 shows an example of a transition from state s to s' through action a . In this example, with $\hat{T} = 4$, we have a small network with $\mathcal{N} = \{1, \dots, 9\}$, with red and green demand nodes, $\mathcal{N}^d = \{1, 2, 3, 4\}$, which are demand nodes with failed and non-failed capital goods, respectively. The remaining five grey nodes are the waiting nodes. Neighboring nodes are nodes that are connected with edges, e.g., $\mathcal{N}_7 = \{5, 6, 8, 9\}$ and $\mathcal{N}_1 = \{5, 6\}$. There are 3 service engineers in this network. In state s , 2 service engineers reside at node 1 and 1 service engineer resides at node 8, hence $y_1(s) = 2$ and $y_8(s) = 1$. Lastly, the capital good at node 1 has failed for 3 time units and the capital good at node 2 for 1 time unit, hence $\sigma_1(s) = 2$ and $\sigma_2(s) = 1$.

The decision maker now decides to reposition two service engineers and repair the failed capital good at node 1 through action a , with $a_1^5 = 1$, $a_8^2 = 1$ and $R_1 = 1$, after which the system transitions to state s' . Next to the changes in $y_i(s') \forall i \in \mathcal{N}$, $\sigma_1(s')$ has made a transition. The service engineer that remained at node 1 has repaired the capital good and therefore $\sigma_1(s') = 0$. Since the capital good at node 2 was not repaired during the transition from state s to s' , $\sigma_2(s')$ has increased with one. Finally, the capital goods at node 3 and node 4 have failed ($\sigma_3(s'), \sigma_4(s') = 1$) during discrete time step Δt .

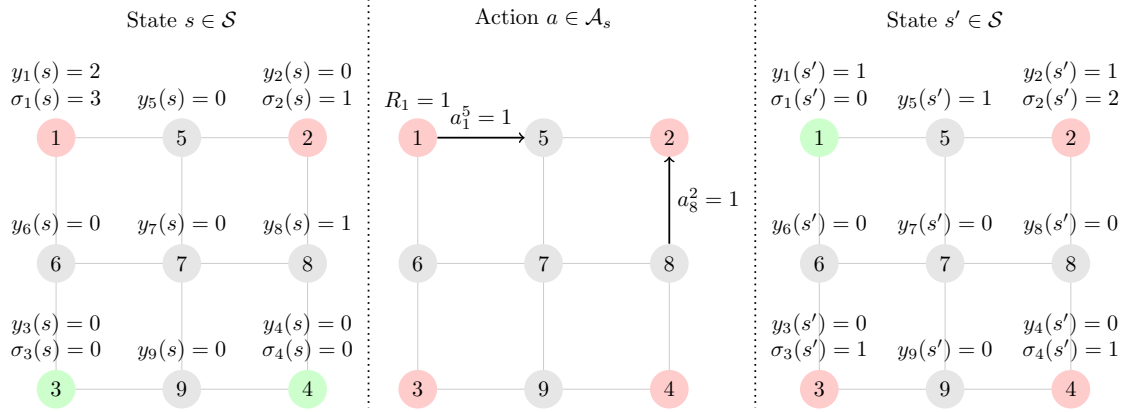


Figure 4.1: Illustration of transition of states

CHAPTER 5

An exact approach

In this chapter, we first describe an exact solution algorithm with which we solve the MPD, as formulated in the previous chapter, to optimality. We will then perform a numerical investigation to gain insights into the structure of the optimal policy. However, as our MDP can only be solved to optimality for small instances due to the curse of dimensionality¹, we will perform this numerical investigation on a small network. These insights will be helpful in developing a scalable heuristic that can be used for larger instances, as we will do in the next chapter.

5.1 Value iteration

In Sections 3.1 and 4.1, we restricted the state space by imposing a logical constraint that ensures that both the state space and the action space are finite. Additionally, the transition cost function (see Section 4, equation (4.7)) is also bounded from above. A stationary average optimal policy exists that can be determined using the value iteration algorithm (Puterman, 2014), if the model would also be unichain². Following the same logic as Olde Keizer et al. (2017), who applied the value iteration algorithm to the joint maintenance and inventory optimization problem, our model can contain multiple recurrent states. If for instance all service engineers reside at a waiting node and the stationary policy (for each state s) is to let all service engineers stay at their node, i.e. $a_i^l = 0 \forall l \in \mathcal{N}_i, \forall i \in \mathcal{N}^w$. Using this policy, each capital good at each node $i \in \mathcal{N}^d$ will be in the failed state $\sigma_i(s) = \hat{T}$ in the long run, and the initial configuration of the service engineers will remain unchanged. The transition matrix corresponding to this action then contains $\binom{|\mathcal{N}^w|+N-1}{|\mathcal{N}^w|-1}$ recurrent states (the number of unique configurations of N service engineers in a network with $|\mathcal{N}^w|$ nodes). Consequently, our model is multichain rather than unichain.

¹The well-known curse of dimensionality refers to the size of both the state space, action space and outcome space that increases rapidly in a high-dimensional MDP like we have formulated in Section 4 (Powell (2007)).

²An MDP is unichain if the transition matrix corresponding to every deterministic stationary policy consists of a single recurrent class and a (possibly empty) set of transient states (Puterman, 2014).

However, as long as the value of α and β in the cost function are positive, it is realistic to assume that any optimal policy repairs a failed capital good at some point in time. This means that our model does satisfy the weak unichain assumption³ as defined in Tijms (1994). As a result, we can find the minimal average cost per time unit and the corresponding optimal policy by applying the value iteration algorithm.

The minimal average cost per time unit, denoted by g^* , is independent of the initial state, and follows from the Bellman optimality equations (see Bellman (1957)) for the (discrete-time) average cost MDP:

$$v^*(s) = \min_{a \in \mathcal{A}_s} \left[C_a(s) + \sum_{s' \in \mathcal{S}} P_a(s, s') \cdot v^*(s') \right] \quad \forall s \in \mathcal{S}, \quad (5.1)$$

where $v^*(s)$ is the optimal value of state s . The optimal stationary policy, denoted by π^* , which consists of the optimal action for each state $s \in \mathcal{S}$, $f^*(s)$, is the policy that attains the minimum in (5.1). Note that action $f^*(s)$ is the action that minimizes the expected value of the resulting state s' .

We solve the fixed-point equations in (5.1) by applying the value iteration algorithm (see Tijms (1994)), which is shown in Algorithm 1. Here v_n denotes the value function obtained with the n -th iteration. Observe that the number of optimality equations grows linearly with the number of states. Hence, the number of optimality equations grows exponentially in the number of demand nodes and/or as a combinatorial number when the total number of nodes and/or number of service engineers grow. As a result, the optimality equations in (5.1) can only be solved for small networks.

Algorithm 1 Value Iteration

Require: $\epsilon > 0$, $n = 0$, $v_0(s) = 0 \forall s \in \mathcal{S}$

1. For each $s \in \mathcal{S}$, compute the value function $v_{n+1}(s)$ as:

$$v_{n+1}(s) := \max_{a \in \mathcal{A}_s} \{ C_a(s) + \sum_{s' \in \mathcal{S}} P_a(s, s') v_n(s') \}$$

and select a stationary policy $f_{n+1}(s)$ which minimizes the value function:

$$f_{n+1}(s) \in \operatorname{argmax}_{a \in \mathcal{A}_s} \{ C_a(s) + \sum_{s' \in \mathcal{S}} P_a(s, s') v_n(s') \}$$

2. Let

$$M_n := \max_{s \in \mathcal{S}} \{ v_n(s) - v_{n-1}(s) \}, \quad m_n := \min_{s \in \mathcal{S}} \{ v_n(s) - v_{n-1}(s) \}$$

stop if $M_n - m_n < \epsilon$, otherwise set $n := n + 1$ and go to step 1

Let f_n denote the stationary policy which minimizes the value function for $n \geq 1$, and let $g_s(f_n)$ denote the corresponding one-step difference $v_n(s) - v_{n-1}(s)$. Since $g_s(f_n)$ is, in the long run, independent of initial state s , we drop the index s and denote it by $g(f_n)$. Then it holds that $m_n \leq g^* \leq g(f_n) \leq M_n$, for all $s \in \mathcal{S}$, where the sequences $\{m_n, n \geq 1\}$ and $\{M_n, n \geq 1\}$ are non-decreasing and non-increasing, respectively (Tijms, 1994). In other words, the sequence $\{v_n(s), n \geq 1\}$ converges to $v^*(s)$ for each $s \in \mathcal{S}$ when n grows large. Additionally, $g(f_n)$, the average cost per time unit resulting from policy f_n , deviates

³For each average cost optimal stationary policy, the associated Markov chain has no two disjoint closed sets (Tijms, 1994).

at most 100ϵ percent from g^* .

5.2 Numerical investigation

In this section, we numerically investigate the structure of the optimal policy obtained with Algorithm 1 with $\epsilon = 10^{-3}$ for a small, tractable region. See Figure 5.1 for the graph representation of the small, tractable region, which consists of a grid with $|\mathcal{N}| = 9$ and $|\mathcal{N}^d| = 4$. We consider two service engineers, i.e. $N = 2$. We use this example throughout this section. Note that the red demand nodes (1 and 4) represent nodes where a capital good has failed, whereas green demand nodes (2 and 3) represent nodes where a capital good is up and running. Furthermore, the black rectangles represent the time a failed capital good has failed (recall that this is equal to $\sigma_i(s)$ in our MDP formulation). For instance, the capital good at node 1 has failed for one time unit, whereas the capital good at node 4 has failed for two time units and \hat{T} is equal to 3. We first investigate the structure of the optimal policy for symmetric instances, where the characteristics of the demand nodes are equal. We then continue with investigating the structure of the optimal policy for asymmetric instances, where the characteristics of the demand nodes differ from each other. All computations were carried out on a PC running Windows (64 bit) with an Intel Quad Core 2.20 GHz processor and 8 GB RAM. The average computation time to calculate g^* for a single instance of this small network is on average equal to approximately 100 minutes.

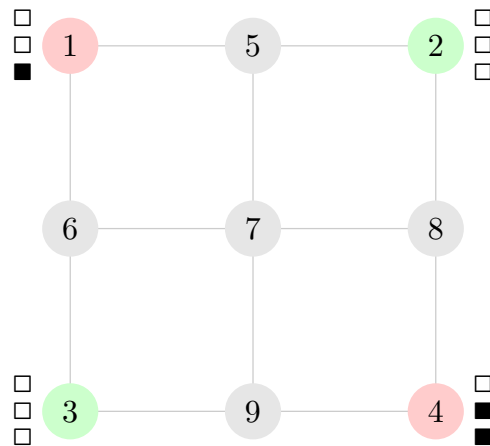


Figure 5.1: A graph representation of the small network under study

We emphasize that instead of characterizing the structure of the optimal policy or determining the performance in terms of the optimal cost rate, we intend to derive insights into how the optimal policy behaves. This is the subject of the remainder of this chapter. We will then use these insights to come up with a scalable heuristic that can be used for larger instances, which is the focus of the next chapter.

5.2.1 Symmetric case

In the symmetric case we set Δt equal to 1 and take $\lambda_i = 0.105 \forall i \in \mathcal{N}^d$, which results in $p_i^0 = 0.1$, $p_i^1 = 0.9 \forall i \in \mathcal{N}^d$. Furthermore, we take two values for $\gamma \in \{0, 0.5\}$, and we subsequently vary the values of α_i , β_i and \hat{T} , where the former two are equal for all nodes $i \in \mathcal{N}^d$ due to symmetry. Note that this choice seems reasonable in practice. Whereas the cost for traveling is rather fixed and relatively small compared to contractual penalties, the costs for service requests whose solution times exceed T and for solving delayed service requests and the solution time threshold depend on the agreement between the service organization and the customer and can thus vary. Moreover, in practice it is not reasonable to set $\beta_i > \alpha_i$ since the primary purpose is mostly to maximize the amount of service requests that are served within T . We therefore choose three combinations ($\alpha_i \gg \beta_i$, $\alpha_i > \beta_i$ and $\alpha_i = \beta_i$) of values for α_i and β_i , that is $(\alpha_i, \beta_i) \in \{(5, 1), (5, 3), (5, 5)\}$. We choose three values for T in our numerical investigation, namely $T \in \{2, 3, 4\}$, which results in 18 test instances. See Table 5.1 for an overview of the parameter settings in the numerical investigation of the symmetric case.

Table 5.1: Parameter settings of numerical investigation of symmetric case

	Input parameter	No. of choices	Values
1	Travel cost, γ	2	0, 0.5
2	Time threshold, T	3	2, 3, 4
3	Cost penalties, (α_i, β_i)	3	(5, 1), (5, 3), (5, 5)

The main observations that can be drawn from the numerical investigation of the symmetric case is that the optimal policies (regardless of the parameter settings in most cases) exhibit similar characteristics with regard to three aspects, which we will discuss in the remainder of this subsection. These three aspects relate to the location strategy for idle service engineers, the dispatching strategy of service engineers that takes into account the state of the system, and the reallocation of service engineers.

Dwell point policy

In warehousing literature, a dwell point policy prescribes the position of idle order-pick equipment (see Rouwenhorst et al. (2000)), which is analogous to a base location policy in DAM literature. The latter refers to positions in an emergency services network where idle ambulances are sent to such that the response times to future emergencies is minimized.

Figure 5.2a shows that whenever there are two idle service engineers, which can best be shown when all demand nodes have capital goods that are up and running, it is optimal to send them to node 6 and node 8 (or node 5 and 9 due to symmetry). Furthermore, Figure 5.2b shows that it is optimal to keep the idle service engineers at node 6 and node 8, if no failure occurs, which makes these two nodes dwell points. This

is also quite intuitive since all demand nodes are reached from there within one time step.

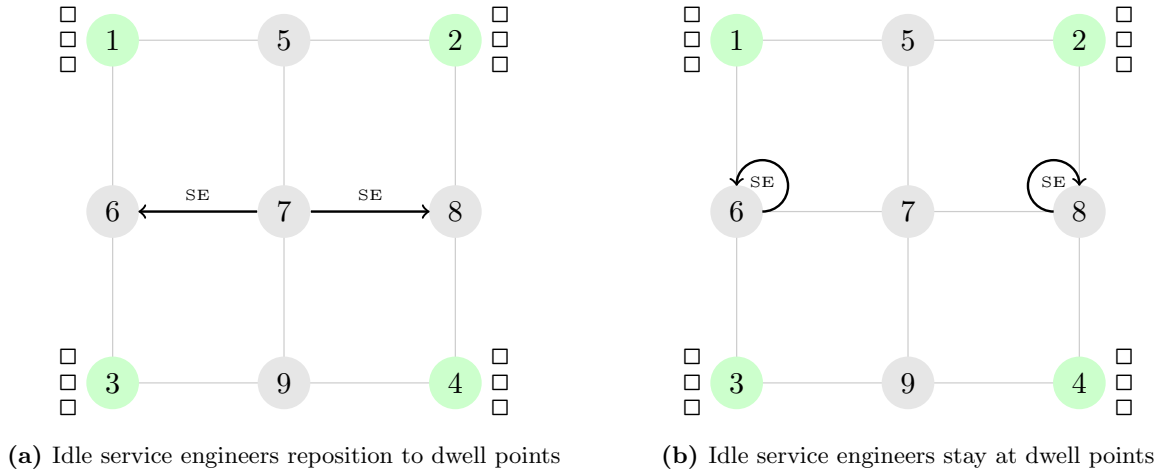


Figure 5.2: Optimal policy exhibits a static dwell point policy

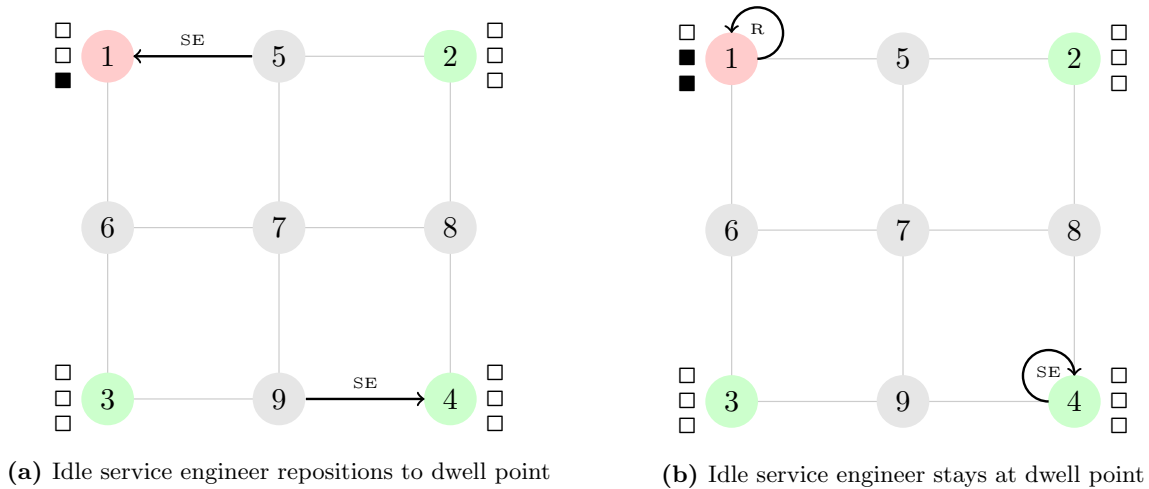


Figure 5.3: Optimal policy exhibits a dynamic dwell point policy

In case a failure occurs at a demand node, Figure 5.3a suggests that dwell points then depend on the state of the system. Here, the optimal policy prescribes that the service engineer from node 5 is sent to node 1, where he will repair the capital good that has failed for 1 time unit, and that the remaining idle service engineer is sent to node 4. Note that the latter action results in that the remaining demand nodes are reached within $2\Delta t$ at maximum, and that the total time to reach the remaining demand nodes is minimized and equal to $4\Delta t$. In the succeeding decision epoch, a repair is carried out at node 1, while the idle service engineer remains at node 4. Thereafter, both service engineers are idle again and if no failure has occurred, then both service engineers will reposition to the static dwell points as is depicted in Figure 5.2. Hence, this illustration of the optimal policy shows that dwell points depend on the current state and that idle service engineers reposition pro-actively to retain a good coverage (i.e. time to reach remaining demand).

Dispatching policy

In practice, a dispatching policy that is often used is the ‘closest-idle first’-policy, where the closest-idle service engineer is sent to an incoming service request. Figure 5.4 shows, however, that the optimal policy can prescribe a different action than sending the closest-idle service engineer. In the state of the system in Figure 5.4a, the capital good at node 1 has failed for two time units, whereas the capital good at node 2 has failed for one time unit. The optimal policy prescribes that the service engineer at node 1 does not repair this capital good, but that he is sent to node 5, such that both failed capital goods can be repaired within \hat{T} . Note that in practice this service engineer would repair this capital good since he is the closest-idle service engineer. Furthermore, this optimal action suggests that the optimal dispatching policy of service engineers to service requests takes into account the state of the system, instead of relying on static policies like the ‘closest-idle first’-policy. This observation is important in designing an efficient dispatching heuristic, which we will see in the next chapter.

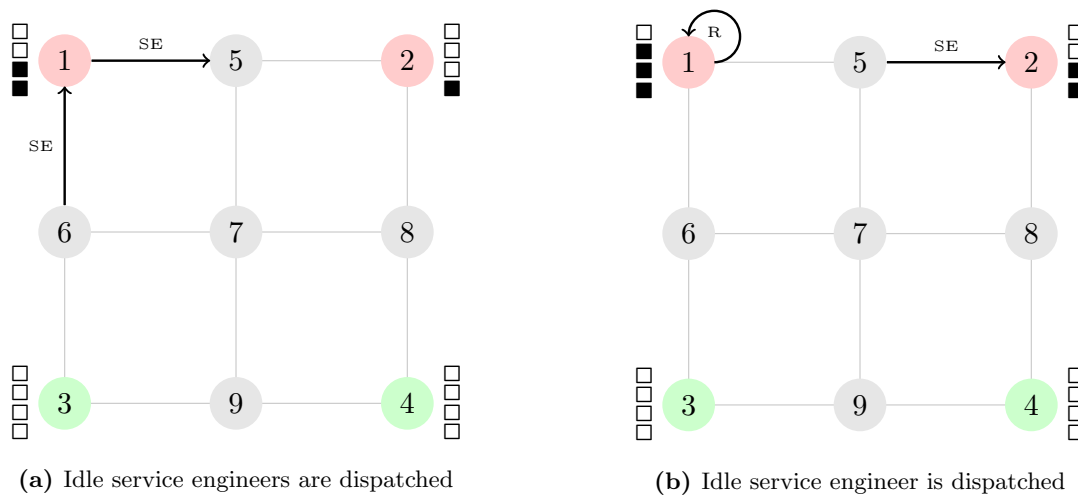


Figure 5.4: Optimal policy exhibits a dynamic dispatching policy

Reallocation

In practice, whenever a service engineer is assigned to a service request, he will be assigned to this service request until he repairs the corresponding capital good. In other words, the service request cannot be postponed anymore and the service engineer that is assigned to it, cannot be reallocated anymore. Figure 5.5 shows that the optimal policy can prescribe to do otherwise. In the first state (see Figure 5.5a), one service engineer is sent to node 3 and one service is sent to node 8, such that they eventually repair the failed capital good at node 3 and node 2, respectively. After this action, during the succeeding time period, the capital good at node 4 also fails. The optimal action (see Figure 5.5b) now prescribes to reallocate and send a service engineer to node 4 to repair this capital good. The reason for this postponement of the service

request at node 2 is that the service engineer cannot make it to repair the capital good at node 2 within \hat{T} (he arrives at node 2 when $\sigma_2 = 3$). Hence, by sending this service engineer to node 4, one repairs at least one capital good within \hat{T} . Even though this action depends on the cost structure and the value of \hat{T} , it suggests that it can be more efficient to remain flexible in reallocating service requests, than to stick to an assignment of service engineers to service requests once it is decided upon. This observation is also useful in designing an efficient dispatching heuristic, which we will see in the next chapter.

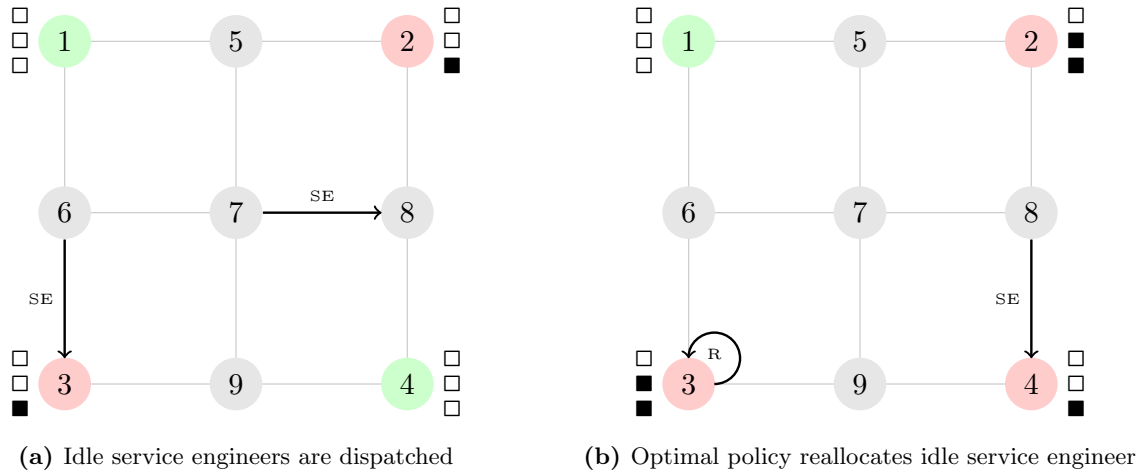


Figure 5.5: Optimal policy exhibits the reallocation of service requests

5.2.2 Asymmetric case

In the asymmetric test bed, we only consider two values for $(\alpha_i, \beta_i) \in \{(5, 1), (15, 3)\}$ and two values for the demand intensity $\lambda_i \in \{0.105, 0.210\}$. We set γ equal to 0.5 and consider three values for T , that is $T \in \{2, 3, 4\}$. We observe that the optimal policy exhibits similar behavior to the symmetric cases, albeit influenced by both the demand and cost parameters.

With respect to dwell points, we observed that, for instance, if we have $(\alpha_i, \beta_i) = (15, 3)$ for $i = 1, 2$ and $(\alpha_i, \beta_i) = (5, 1)$ for $i = 3, 4$ and equal demand intensities for all demand nodes, both service engineers, when idle, reside at node 5. Similarly, when we have $\lambda_i = 0.210$ for $i = 1, 2$ and $\lambda_i = 0.105$ for $i = 3, 4$ and equal values for the cost parameters for all demand nodes, both service engineers, when idle, also reside at node 5. This suggests, which is also quite intuitive, that the locations of the dwell points point policy is influenced by both cost and demand parameters of the demand nodes. More specifically, idle service engineers move towards demand nodes that have either high penalty costs or a high demand intensity, or both. In the next chapter, we will see that our devised reposition heuristics, both dynamic and static, explicitly take into account both cost and demand parameters of the demand nodes.

With respect to the dispatching policy and the fact that the optimal policy exhibits reallocation, we observed

similar actions as extensively discussed in the symmetric case. In contrast to the dwell point policy, where the influence of the demand and cost parameters was easy to observe, it was less obvious to determine how the dispatch and reallocation policy is influenced by the parameters. Although we observed, for instance, that service engineers are first dispatched to demand nodes with high cost penalties and then to demand nodes with low cost penalties if both exist at the same time, we are not able to give specific examples like we provided in the previous section. This is mainly due to the fact that it is unclear when the optimal action is due to cost parameters, demand parameters, or both, or just because of the combination of timing of failures and the current configuration of the service engineers. We therefore conclude this numerical investigation and we design our heuristics based on the characteristics of the optimal policy that we discussed before.

Heuristic approaches

In the previous chapter, we solved the dispatch and reposition problem using an exact approach by solving the MDP to optimality. However, due to the curse of dimensionality, we cannot use this method for problems of practical size. Hence, we intend to use the derived insights from the previous chapter to derive scalable heuristics that can be used for larger instances.

Although the MDP solves both the dispatch and reposition problem in an integrated way, we decompose the problem into two sub-problems and design a heuristic independently for both the dispatching and repositioning sub-problems. Note that this is also common in practice, where managers at service organizations are faced with two main problems in real-time: a dispatching problem and reposition problem.

In this chapter, we start with discussing the dispatching sub-problem and we finish with addressing the repositioning sub-problem. For both sub-problems, we derive a static heuristic and a dynamic heuristic. Our static heuristics are characterized by rules of thumbs that are determined a-priori and which are then always followed, regardless of the current state of the network. By contrast, our dynamic heuristics are characterized by maximizing a goal function that takes into account information about the current state of the network. We conclude this section by discussing how we solve the real-time dispatch and reposition problem of service engineers by applying our proposed heuristics (either the static or dynamic variant) for both sub-problems in a consecutive manner. Here, we also differentiate between whether reallocation is allowed or not in the policy. This has implications for the definition of ‘idle’ that we use in the discussions of our proposed heuristics in the remainder of this chapter. When reallocation is not allowed, ‘idle’ service engineers are service engineers that arrived at their final destination or have completed a repair in the preceding time step and become eligible for dispatching and repositioning decisions again in the succeeding decision epoch. In contrast, when reallocation is allowed, at every decision epoch, the whole fleet of service engineers is ‘idle’, regardless of whether they are on their way to their destination or have already reached their destination.

6.1 Dispatching

The numerical investigation in Section 5.2 suggests that the optimal policy exhibits a dispatching policy that takes into account all service engineers, when deciding upon which service engineer must be dispatched to each waiting service request. In other words, the current state of the system is taken into account, rather than solely relying on static decision rules that do not take into account state information. However, the former is computationally more expensive than the latter.

In this subsection we discuss two dispatching heuristics. We start with briefly discussing a static heuristic that is often encountered in practice. We then discuss a dynamic counterpart, where we take all idle service engineers and (a subset of) all waiting service requests into account when determining which service engineer is dispatched to each waiting service request.

6.1.1 Static

A dispatching heuristic that is both intuitive and easy to implement is called the ‘closest-idle first’-heuristic. Because of these two characteristics, this heuristic is often used in practice, which was also confirmed by our interviews at our industrial partner, a large manufacturer of industrial printers. In this heuristic, whenever a service request arrives, the closest service engineer that is idle is sent to this service request. If multiple service requests arrive at the same time, then each next service request is selected with equal probability to which the closest-idle service engineer will be dispatched. We will also use this heuristic as the benchmark to compare our proposed dynamic dispatching heuristic to, which we will discuss in the next subsection.

Observe that even though this heuristic is often used in practice, it does not incorporate the state of the capital goods of the corresponding waiting service requests, and hence it does not differentiate between waiting service requests. It could thus be possible that a service request, that lies very remote from the nearest idle service engineer, has to wait for a very long time, thereby incurring costs, if other service requests arrive constantly that lie closer to the idle service engineers. This undesirable situation can be prevented by taking into account the state of the failed capital goods that correspond to the waiting service requests in the dispatching heuristic.

6.1.2 Dynamic

The problem of dispatching service engineers to waiting service requests, while taking into account the distance to and the characteristics of the waiting service requests, shows similarities with a well-known assignment problem: the Minimum Weighted Bipartite Matching problem (MWBM).

To this end, we introduce a weighted complete bipartite graph $G = (V_1, V_2, E, l)$, where the two partitions V_1, V_2 are the two node sets, E the edge set and l a function assigning weights to edges. The node set V_1 corresponds to the locations of the idle service engineers. To each idle service engineer we introduce a node indexed by its location (if there are more service engineers at a location, we use subindices to differentiate between them). Similarly, the node set V_2 consists of the nodes where a capital good is currently failed. Let $v_1 \in V_1$ and $v_2 \in V_2$, then $l((v_1, v_2))$ assigns a non-negative real-valued weight to edge $(v_1, v_2) \in E$ as follows:

$$l((v_1, v_2)) = (d(v_1, v_2) - \sigma(v_2))^+, \quad (6.1)$$

where $x^+ = \max(0, x)$, $d(v_1, v_2)$ is the Manhattan distance¹ (since we have a grid) between v_1 and v_2 and $\sigma(v_2)$ is the failed state of the capital good at node v_2 (which corresponds to $\sigma_{v_2}(s)$ in the MDP formulation). Hence, $l : E \rightarrow \mathbb{R}_0^+$. Note that this mapping ensures that the longer a capital good has failed or the closer it is located to a service engineer, or both, the higher the priority this capital good has to dispatch a service engineer to it. This is exactly the mechanism that we want to attain with our dynamic dispatching heuristic, since we want to minimize costs that are associated with both delayed services and traveling.

A matching $M \subseteq E$ is a collection of edges such that no two edges share an endpoint. Furthermore, a matching is perfect if $|M| = |V_1| = |V_2|$ and let \mathcal{M} be the set of all perfect matchings. Note that our dynamic dispatching problem (*DDP*) can then be formulated as the following MWBM:

$$(DDP) \quad \min_{M \in \mathcal{M}} \sum_{e \in M} l(e), \quad (6.2)$$

Observe that it could be possible that $|V_1| > |V_2|$ or $|V_1| < |V_2|$. In that case, we insert into the relevant partition (the partition with the lowest cardinality) dummy nodes with ∞ -weight edges to all nodes in the opposite partition. By solving problem (*DDP*), we can find the optimal allocation of idle service engineers to the waiting service requests. We use the Hungarian algorithm, which runs in $\mathcal{O}(\max\{|V_1|^3, |V_2|^3\})$ (Jungnickel, 2008), to solve problem (*DDP*) to optimality. We refer the reader to Jungnickel (2008) for an extensive discussion of the Hungarian algorithm. During the interviews with service engineer planners at our industrial partner, it became clear that the service logistic networks at which this research focuses typically employ around 20-30 service engineers and contain 120-130 demand nodes. Therefore, the maximum value that $\max\{|V_1|^3, |V_2|^3\}$ can attain, remains also relatively small and hence the Hungarian algorithm can be used to make instant dispatching decisions. Hence, the dynamic dispatching heuristic is well-scalable

¹The Manhattan distance between two points in a grid is based on a strictly horizontal and/or vertical path (that is, along the grid lines), as opposed to the diagonal or ‘as the crow flies’ distance. The Manhattan distance is equal to the sum of the horizontal and vertical components.

according to our definition of scalability.

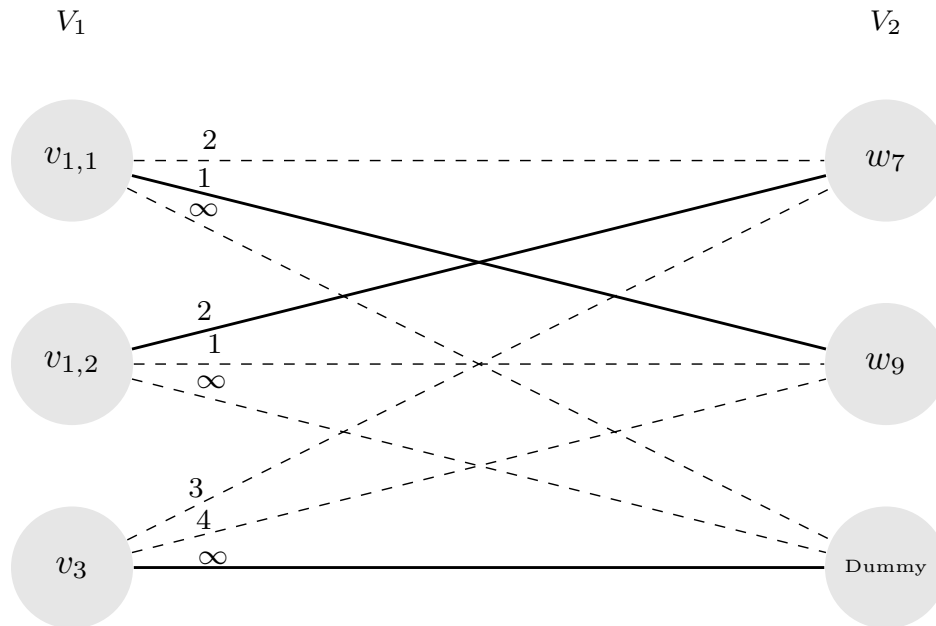


Figure 6.1: Example of solution to dynamic dispatching problem

Figure 6.1 shows an example of an assignment that results from solving problem (*DDP*). In this example, there are three idle service engineers: two at location 1 and one at location 3. These idle service engineers are indexed by their location (where we use a subindex, i.e. $v_{1,1}$ and $v_{1,2}$, for the two service engineers at location 1) and partitioned in the set V_1 . We have two waiting service requests: one for location 7 and one for location 9. Since $|V_1| > |V_2|$, we add a dummy waiting service request to partition V_2 with ∞ -weight edges to the three elements of V_1 . In this example, we set $d(v_{1,1}, w_7) = d(v_{1,2}, w_7) = 3$, $d(v_{1,1}, w_9) = d(v_{1,2}, w_9) = 5$, $d(v_3, w_7) = 4$ and $d(v_3, w_9) = 8$ (note that these are just artificial values for illustrative purpose and that we could have taken other values as well that result in the same weights). The capital good at location 7 and the capital good at 9 have failed for 1 and 4 time units, respectively. Our weight function (6.1) now assigns the weight to the edges between the elements (excluding dummy elements) of partition V_1 and V_2 (see Figure 6.1 for the resulting weights). Solving problem (*DDP*), results in a matching between $v_{1,1}$ and w_9 , $v_{1,2}$ and w_7 , and v_3 and the dummy service request. Hence, service engineer 1 is dispatched to location 9, service engineer 2 is dispatched to location 7, whereas service engineer 3 remains idle and becomes eligible for repositioning.

6.2 Repositioning

The numerical investigation in Section 5.2 suggests that the optimal policy exhibits a dwell point policy. This means that idle service engineers are repositioned by sending them to dwell points in anticipation of future

demand. We also saw that the location of these dwell points can depend on the state of the system. This suggests that the optimal policy exhibits a dwell point policy that is dynamic, rather than static. However, for problems of practical size it is computationally expensive to take into account the whole state of the system when reposition decisions have to be made instantly. In this subsection we discuss two repositioning heuristics. We start with a static repositioning heuristic, where we determine the location of the dwell points a priori, after which we send each idle service engineer to the closest dwell point. We then discuss a dynamic variant, where the locations of the dwell points are not determined a priori.

6.2.1 Static

In a static repositioning policy, we search for static dwell points where idle service engineers are being sent to in anticipation of future demand, and we want to determine the maximum number of service engineers that can occupy a dwell point at the same time. This is also a common heuristic in practice. In fact, during interviews with service engineers planners at our industrial partner, it became clear that the planners indeed send each idle service engineer to the nearest so-called waiting location (an equivalent term for dwell points). However, at our industrial partner, these waiting locations are determined based on the physical characteristics of the location (for instance, some waiting locations were the homes of service engineers). On the contrary, we determine dwell points and the maximum number of service engineers that can occupy each dwell point at the same time such that we incorporate how well idle service engineers can serve future service requests.

We use the notion of coverage as a measure for how well or how bad future demand is anticipated to, since it is intuitive that a well-covered service region outperforms a not so well-covered service region in anticipating future service requests. The sub-problem of finding dwell points, and their capacity, where idle service engineers are sent to, such that the weighted expected coverage is maximized, can then be seen as a stochastic variant of the maximal covering location problem, called the Maximum Expected Covering Location Problem (MEXCLP) (Daskin, 1983).

In the MEXCLP, we have N service engineers that need to be positioned over a set of possible dwell points \mathcal{N} , hence a demand node can also be a dwell point. A service engineer can be either idle or busy. Let $q \in [0, 1]$ be the probability that a service engineer is busy. Note that it is implicitly assumed that this probability is the same for all service engineers and independent of their position with respect to the demand and the other service engineers. We calculate this probability by dividing the total expected load of the network by the number of service engineers, that is:

$$q = \min\left\{\frac{\sum_{i \in \mathcal{N}^d} p_i^0}{N}, 1\right\} \quad (6.3)$$

Here we do not take into account the length of an occupied period when a service engineer is actually busy. Since we use q both when reallocation is and when reallocation is not allowed, the busy period will vary and therefore it is difficult to take into account the busy period. To simplify the calculation, we neglect the busy period. We introduce the decision variable x_j which represents the capacity of node $j \in \mathcal{N}$. Next, we introduce the set W_i for all $i \in \mathcal{N}^d$, which is the set of nodes that cover demand node i . With cover we mean that if a service engineer is positioned at node $j \in W_i$ and the capital good at node i fails, then node i can be reached within $\hat{T} - 1$ time steps by this service engineer, and hence be repaired within \hat{T} time steps. More formally, we have $W_i = \{j \in \mathcal{N} | d(j, i) \leq \hat{T} - 1\}$. Furthermore, we introduce a binary variable y_{ik} that is equal to 1 if and only if node $i \in \mathcal{N}^d$ is covered by at least k service engineers. The expected covered demand of node i given that exactly k service engineers cover this node, denoted by E_k^i , is calculated as follows:

$$\begin{aligned} E_k^i &= \lambda_i \cdot P(\text{at least 1 out of } k \text{ service engineers is idle}) \\ &= \lambda_i \cdot (1 - P(k \text{ service engineers are busy})) \\ &= \lambda_i \cdot (1 - q^k) \end{aligned} \tag{6.4}$$

The expected weighted covered demand of node i given that exactly k service engineers cover this node, denoted by \hat{E}_k^i , is then equal to $(\alpha_i + \beta_i) \cdot E_k^i = (\alpha_i + \beta_i) \cdot \lambda_i \cdot (1 - q^k)$

Our static repositioning problem (*SRP*) can then be formulated as the following weighted MEXCLP:

$$(SRP) \quad \max \quad \sum_{i \in \mathcal{N}^d} \sum_{k=1}^N (\alpha_i + \beta_i) \cdot \lambda_i (1 - q)^{k-1} y_{ik} \tag{6.5}$$

$$\text{subject to} \quad \sum_{j \in \mathcal{N}} x_j \leq N, \tag{6.6}$$

$$\sum_{j \in W_i} x_j \geq \sum_{k=1}^N y_{ik}, \quad \forall i \in \mathcal{N}^d \tag{6.7}$$

$$x_j \in \{0, \dots, N\}, \quad \forall j \in \mathcal{N} \tag{6.8}$$

$$y_{ik} \in \{0, 1\}, \quad \forall i \in \mathcal{N}^d, \forall k \in \{0, \dots, N\} \tag{6.9}$$

The objective function (6.5) sums the total expected weighted coverage. Here we assign weight $(\alpha_i + \beta_i)$ to the expected coverage of each demand node $i \in \mathcal{N}^d$. This ensures that if node i has higher costs for delayed services, then the expected coverage of this node has more priority than nodes with lower costs for delayed services. In practice, this means that (more) dwell points will lie closer near demand nodes that have high costs for delayed services. Consequently, such a demand node has a higher chance of being repaired within T time units, as soon as the capital good fails, which leads to lower costs than when you would not take this

weight into account in determining dwell points.

Equation (6.6) states that at most N service engineers are to be positioned. This Equation will be binding in general. Equation (6.7) ensures that if node $i \in \mathcal{N}^d$ is covered by at least k service engineers, then the sum of all service engineers that are located at a node $j \in W_i$ is at least k . Furthermore, Equation (6.8) imposes the logical integral constraint that we can only position between 0 and N service engineers at a node. Finally, Equation (6.9) ensures that variable y_{ik} can only take value 0 or 1.

6.2.2 Dynamic

In the previous subsection, we discussed the notion of coverage, and subsequently discussed a related model that we can use to determine static dwell points, where service engineers are sent to when they are idle. Daskin (1983) showed that the marginal coverage contribution of the k^{th} service engineer to the expected value of the covered demand of node i is equal to $E_k^i - E_{k-1}^i = \lambda_i \cdot (1-q)q^{k-1}$. Hence, the weighted marginal coverage contribution of the k^{th} service engineer to the expected value of the covered demand of node i is equal to $\hat{E}_k^i - \hat{E}_{k-1}^i = (\alpha_i + \beta_i) \cdot \lambda_i (1-q)q^{k-1}$. Consequently, if a service engineer is sent to node j where he will become the k^{th} service engineer, then the total marginal coverage contribution of this service engineer to the total expected covered demand (of the demand nodes where the capital good is still up and running) is equal to $\sum_{i \in \{x \in W_j | \sigma_x = 0\}} = \hat{E}_k^i - \hat{E}_{k-1}^i$.

Based on this observation, we can now design the following repositioning heuristic: At each decision epoch, we sent each idle service engineer to the neighboring node, or let him remain at the current node, with the highest total weighted marginal coverage contribution to the total covered demand. That is, send each service engineer that is currently at node i to (or let him remain at) node j such that $j \in \operatorname{argmax}_{n \in \mathcal{N}_i \cup \{i\}} \left\{ \sum_{l \in \{x \in W_n | \sigma_x = 0\}} \hat{E}_k^l - \hat{E}_{k-1}^l \right\}$.

Note that, if we have n idle service engineers, then the maximum size of the search space of this local search heuristic is equal to 5^n . This is because the decision to send a service engineer to a neighboring node could depend, because of the marginal coverage contribution, on whether it is already decided to send another service engineer to this particular node in the same decision epoch. We deal with this by randomly selecting the next service engineer in the set of idle service engineers for which we still need to decide where to sent these service engineers. Consequently, we do this for each idle service engineer until a decision has been made for each idle service engineer at a particular decision epoch. This reduces the maximum cardinality of the search space to $n \cdot 5$, which is suitable for making reposition decisions in real-time in networks of real-life size when n becomes large. As a result, the dynamic repositioning heuristic is well-scalable according to our definition of scalability.

6.3 Heuristic policies

In the two previous subsections, we extensively elaborated on the static and dynamic heuristics for both the sub-problem of dispatching and repositioning, respectively. Next to these heuristics, we can also differentiate between the case where reallocation is possible and where it is not. In practice, which was also confirmed by the production planners at our industrial partner, once service engineers are dispatched or sent to a dwell point they become available for dispatching or repositioning again when they reach their destination. In contrast, the numerical investigation of the optimal policy in Section 5.2.1 suggests that the optimal policy does reallocate service engineers even before they reach their destination. In essence, reallocation leads to being considerably more flexible in deviating from previous dispatch and reposition decisions. Combining the option of whether or not reallocating with two options each for both the dispatching and repositioning sub-problem, we have eight heuristics in total. Table 6.1 presents an overview of these eight heuristic policies, ranging from myopic (SDSR heuristic) to advanced (DDDR-R heuristic).

Table 6.1: Overview of eight heuristics

	Name	Dispatching	Repositioning	Reallocating
1	SDSR	Static	Static	
2	SDSR-R	Static	Static	✓
3	SDDR	Static	Dynamic	
4	SDDR-R	Static	Dynamic	✓
5	DDSR	Dynamic	Static	
6	DDSR-R	Dynamic	Static	✓
7	DDDR	Dynamic	Dynamic	
8	DDDR-R	Dynamic	Dynamic	✓

Each heuristic consist of two consecutive steps that are carried out at the start of each time period Δt :

1. A central decision maker determines which idle service engineers are dispatched to the waiting service requests by using the dispatch heuristic. If reallocating is allowed, the size of the set of idle service engineers is equal to N . If reallocating is not allowed, then the set of idle service engineers consists of all service engineers that arrived (and possibly finished a repair) at their destination at the end of the previous time period.
2. If there are still idle service engineers after having dispatched service engineers to all waiting service requests, the central decision maker determines for each idle service engineer where to sent them to next. This corresponds to solving the reposition sub-problem.

Observe that if reallocating is allowed, multiple paths with the same Manhattan distance exist, where each path can have a different performance in the end. Namely, if a service engineer is sent from node with coordinates $(0, 0)$ on the grid, to a node with coordinates (m, n) on the grid, then there exist $\binom{m+n}{m}$ different

paths. We overcome this by randomly selecting, at the start of each time step, the next node with equal probability.

Finally, if reallocating is allowed, then there is not an explicit repair decision. In contrast, if reallocating is not allowed, then the decision to dispatch a service engineer from node x to a service request at node y also implies that this failed capital good will be repaired after $d(x, y) + 1$ time units (note that $\Delta t = 1$). Therefore, if after the dispatching decision, service engineers are dispatched to nodes where they are already residing, then this means that a repair will be carried out by them in the upcoming time period.

Computational study

In this chapter, we present both a small and large computational study to evaluate the performance of the heuristics that we discussed in the previous chapter. We first introduce the test beds and objectives. Subsequently, we present and discuss the results of the computational study.

7.1 Test beds and objectives

We first discuss the small test bed, which compares the performance of the heuristics with the performance of the optimal policy. We then conclude this section with discussing the large test bed, where we consider real-life networks of industrial size.

7.1.1 Small test bed

In the small test bed, we consider the network as discussed in Section 5.2. As discussed before, it is well-known that solving MDPs suffers from the curse of dimensionality; We therefore resort to test instances that are rather small such that they can be solved within reasonable time.

The small test bed serves three objectives. First, we want to determine which heuristic performs best compared to the optimal policy. Second, we want to quantify the gap between the performance, in terms of the cost rate, of the optimal policy, denoted by g^* , obtained by Algorithm 1 with $\epsilon = 10^{-3}$ and the cost rate obtained by heuristic n , denoted by g^n . We calculate this relative difference as follows:

$$\%GAP = 100 \cdot \frac{g^n - g^*}{g^*}, \quad (7.1)$$

where g^n is obtained by performing a simulation study using the technique of Discrete Event Simulation (DES). Third, we want to investigate how the answers to the first two objectives are influenced by different

parameter settings.

We consider two test beds of small instances, one with symmetric demand intensities and cost parameters (where demand intensities and cost parameters are identical for all demand nodes) and one with asymmetric demand intensities and cost parameters (where demand intensities and cost parameters vary across the demand nodes). In the former, we consider five different demand intensities for each demand node $i \in \mathcal{N}^d$, $\lambda_i \in \{0.15, 0.20, 0.25, 0.30, 0.35\}$. Next, we consider two different values for the solution time threshold, that is $\hat{T} \in \{3, 4\}$. Finally, with regard to the cost parameters, we consider three different values for γ , i.e. $\gamma \in \{0.50, 0.75, 1.00\}$, and three different combinations for $(\alpha_i, \beta_i) \in \{(8, 4), (8, 6), (8, 8)\}$. These parameter settings result into $5 \cdot 2 \cdot 3^2 = 90$ instances. Table 7.1 summarizes the input parameter settings used in the small symmetric test bed.

Table 7.1: Parameter settings of small symmetric test bed

	Input parameter	No. of choices	Values
1	Demand intensity, λ_i	5	0.15, 0.20, 0.25, 0.30, 0.35
2	Solution time threshold, \hat{T}	2	3, 4
3	Travel cost, γ	3	0.50, 0.75, 1.00
4	Cost penalties, $(\alpha_i, \beta_i), \forall i \in \mathcal{N}^d$	3	(8,4), (8,6), (8,8)

In the small asymmetric test bed, we generate the demand intensity for each node $i \in \mathcal{N}^d$ from an uniform distribution $U[0.15; 0.35]$. Next, since we cannot perform a full factorial test bed in which we consider different cost parameters for each demand node, simply due to the time complexity of solving one instance to optimality, we consider only extremes where we only vary the cost parameters of one demand node. This test bed can thus be regarded as a pessimistic test bed. To that end, we consider four cost penalty combinations for demand node 1, that is $(\alpha_1, \beta_1) \in \{(4, 2), (8, 4), (12, 6), (20, 10)\}$, whereas we consider the same three different combinations for (α_i, β_i) as in the small symmetric test bed for demand node $i \in \{2, 3, 4\}$. These parameter settings result into $1 \cdot 2 \cdot 3^2 \cdot 4 = 72$ instances. Table 7.2 summarizes the input parameter settings used in the small asymmetric test bed.

Table 7.2: Parameter settings of small asymmetric test bed

	Input parameter	No. of choices	Values
1	Demand intensity, λ_i	1	$U[0.15; 0.35]$
2	Solution time threshold, \hat{T}	2	3, 4
3	Travel cost, γ	3	0.50, 0.75, 1.00
5	Cost penalties, (α_1, β_1)	4	(4,2), (8,4), (12,6), (20,10)
4	Cost penalties, $(\alpha_i, \beta_i), \forall i \in \{2, 3, 4\}$	3	(8,4), (8,6), (8,8)

7.1.2 Large test bed

In the large test bed, we consider real-life networks of industrial size. Due to the size of the networks, we cannot compare the performance of our heuristics with the optimal cost rate. We therefore compare the performance of the heuristics with the performance of a benchmark heuristic. The benchmark heuristic can be seen as what is now common in practice.

As said before, during our interviews with the service engineers planners at our industrial partner, we observed that they use the closest-idle heuristic for dispatching service engineers and that they send idle service engineers to dwell points that are determined a priori, where they do not take into account state information. Moreover, to simplify the planning process, the service engineers planners do not reallocate service engineers after decisions are made. In essence, this coincides with our first heuristic, the SDSR heuristic (see Section 6.3).

We can then quantify the value that can be attained in practice when using heuristic $n \in \{2, 3, \dots, 8\}$ instead of this benchmark. That is

$$\%VAL = -100 \cdot \frac{g^n - g^1}{g^1}, \quad (7.2)$$

where %VAL will indicate how much cost per time unit reductions in percentages can be attained when using heuristic n instead of the SDSR heuristic.

Analogously to the small test bed, we consider two test beds of large instances, where both are a squared grid network, one with symmetric cost parameters (where cost parameters are identical for all demand nodes) and one with asymmetric cost parameters (where demand intensities and cost parameters vary across the demand nodes). Note that we have asymmetric demand intensities in both test beds, since this is also the case in practice. Furthermore, since we want to evaluate our heuristics under circumstances that are comparable to circumstances that are encountered in practice, we have to choose the values for the parameters with caution. For instance, if we choose a network with 100 demand nodes, then the total number of nodes $|\mathcal{N}|$, the number of service engineers N and our solution time threshold \hat{T} , should be different than when we choose a network with 180 demand nodes, since this will also be the case in practice. To deal with this, we choose the values for the other parameters relatively to the number of demand nodes in our network since this is the most important characteristic that determines whether a network is of practical size or not. We consider two values for the number of demand nodes, that is $|\mathcal{N}^d| \in \{100, 180\}$, which is confirmed to be of of practical size in the interviews at our industrial partner. With regard to the total number of nodes, we choose two values for the number of nodes in both sides of our grid network: $0.4 \cdot |\mathcal{N}^d|$ and $0.6 \cdot |\mathcal{N}^d|$. Consequently, we have also two values for $|\mathcal{N}|$, that is $|\mathcal{N}| \in \{(0.4 \cdot |\mathcal{N}^d|)^2, (0.6 \cdot |\mathcal{N}^d|)^2\}$. This means that if a network contains 100 demand nodes, then the total number of nodes is either 1600 or 3600.

We also choose to randomly distribute the demand nodes over the squared grid network. We generate values from a uniform distribution for the demand intensities for each demand node $i \in \mathcal{N}^d$, that is $\lambda_i \in \{U[0.001; 0.01], U[0.01; 0.05]\}$. For the number of service engineers N , we consider two different values that are set as an integral fraction $N \in \{\lfloor \frac{1}{10} \cdot |\mathcal{N}^d| \rfloor, \lfloor \frac{1}{5} \cdot |\mathcal{N}^d| \rfloor\}$ of the number of demand nodes. In order to determine solution time thresholds that are representable for practice, we reason along the following lines. If we have a squared grid with sides of length $\sqrt{|\mathcal{N}|}$ and hence a surface of $|\mathcal{N}|$, then each service engineer, if we distribute them evenly, is responsible for a sub-region with surface $\frac{|\mathcal{N}|}{N}$. Such a sub-region has sides of length $y = \sqrt{\frac{|\mathcal{N}|}{N}}$, which means that it takes $y - 1$ time units to cross the whole region, i.e. from one side to the opposite side of the sub-region. Since the total number of nodes in our network is relatively large, we neglect minus 1, and consider values for \hat{T} that are multiples of y rounded to the nearest integer, that is $\hat{T} \in \{\lceil 1 \cdot y \rceil, \lceil 1.5 \cdot y \rceil\}$. We test two different values for γ ($\gamma \in \{1, 4\}$), two different values for α_i ($\alpha_i \in \{50, 500\}$) and we consider two different values that are set as a fraction of α_i for β_i , i.e. $\beta_i \in \{0.05 \cdot \alpha_i, 0.1 \cdot \alpha_i\}$ for each node $i \in \mathcal{N}^d$. All cost parameters are in euros and during discussions with our industrial partner it was confirmed that penalty costs of this ratio are realistic. These parameter settings result into $2^8 = 256$ instances. Table 7.3 summarizes the input parameter settings used in the large symmetric test bed.

The parameter settings are chosen in such a way that they reflect realistic situations. For instance, if a service region in reality is a square with sides of length 320km, then we have the following. With a grid network with \mathcal{N}^d and sides of length $0.4 \cdot |\mathcal{N}^d|$, we have that the length of an edge is equal to 8km. If service engineers are traveling at a speed of 80km/hr (on average, service engineers travel in both rural and urban areas), Δt equals 6 minutes. With 20 service engineers and \hat{T} equal to 9 (which corresponds to 54 minutes in practice), we can approximate the average utilization of the service engineers for both the instances with $U[0.001; 0.01]$ and $U[0.01; 0.05]$ as follows. For $U[0.001; 0.01]$, we have on average $100 \cdot \frac{0.001+0.01}{2} = 0.55$ failures per time step. If such a failure needs on average 6 discrete time steps before it is solved, then we approximate the utilization, denoted by ρ in the whole network as follows: $\rho = \frac{\text{work offered per time step}}{\text{capacity}} = \frac{0.55 \cdot 10}{20} = 0.275$. Similarly, for $U[0.01; 0.05]$ we have $\rho = \frac{3 \cdot 10}{20} = 0.900$. Other instances result in either higher or lower values for the approximate utilization, and hence our test captures instances that are not only realistic but also capture a wide continuum for the degree of utilization.

Table 7.3: Parameter settings of large symmetric test bed

	Input parameter	No. of choices	Values
1	Number of demand nodes, $ \mathcal{N}^d $	2	100, 180
2	Number of nodes, $ \mathcal{N} $	2	$(0.4 \cdot \mathcal{N}^d)^2, (0.6 \cdot \mathcal{N}^d)^2$
3	Demand intensity, $\lambda_i, \forall i \in \mathcal{N}^d$	2	$U[0.001; 0.01], U[0.01; 0.05]$
4	Number of service engineers, N	2	$\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, \lfloor \frac{1}{5} \cdot \mathcal{N}^d \rfloor$
5	Solution time threshold, \hat{T}	2	$\lceil 1 \cdot \sqrt{\frac{ \mathcal{N} }{N}} \rceil, \lceil 1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}} \rceil$
6	Travel cost (euros), γ	2	1, 4
7	Cost penalty (euros), $\alpha_i, \forall i \in \mathcal{N}^d$	2	50, 500
8	Cost penalty (euros), $\beta_i, \forall i \in \mathcal{N}^d$	2	$0.05 \cdot \alpha_i, 0.1 \cdot \alpha_i$

In the asymmetric, we generate the value of α_i for each demand node i from a uniform distribution, that is $\alpha_i \in \{U[50; 100], U[100; 500]\}$. The other parameters are set in the same way as for the first large test bed and hence, test bed 2 also results in 256 instances. Table 7.4 summarizes the input parameter settings used in the large asymmetric test bed.

Table 7.4: Parameter settings of large asymmetric test bed

	Input parameter	No. of choices	Values
1	Number of demand nodes, $ \mathcal{N}^d $	2	100, 180
2	Number of nodes, $ \mathcal{N} $	2	$(0.4 \cdot \mathcal{N}^d)^2$, $(0.6 \cdot \mathcal{N}^d)^2$
3	Demand intensity, λ_i , $\forall i \in \mathcal{N}^d$	2	$U[0.001; 0.01]$, $U[0.01; 0.05]$
4	Number of service engineers, N	2	$\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $\lfloor \frac{1}{5} \cdot \mathcal{N}^d \rfloor$
5	Solution time threshold, \hat{T}	2	$\lfloor 1 \cdot \sqrt{\frac{ \mathcal{N} }{N}} \rfloor$, $\lfloor 1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}} \rfloor$
6	Travel cost, γ	2	1, 4
7	Cost penalty, α_i , $\forall i \in \mathcal{N}^d$	2	$U[50; 100]$, $U[100; 500]$
8	Cost penalty, β_i , $\forall i \in \mathcal{N}^d$	2	$0.05 \cdot \alpha_i$, $0.1 \cdot \alpha_i$

7.2 Numerical results

Both the exact approach and the DES study are programmed as single threaded applications in JAVA. Furthermore, we use a Branch and Cut implementation of the open source package GLPK implemented in JAVA to solve problem (*SRP*). All computations were carried out on a PC running Windows (64 bit) with an Intel Quad Core 2.20 GHz processor and 8 GB RAM. The average computation time to calculate g^* for a single instance of the small test bed is on average equal to approximately 100 minutes, which is also an argument for the limited number of instances and the size of the instances itself in this small test bed.

In the small test bed, we evaluate each heuristic with 10 simulation runs of 30,000 simulated decision epochs, from which we discard the first 5,000 decision epochs due to the warm-up effect. In the large test bed, we observe that it takes longer before convergence is reached. Hence, we evaluate each heuristic with 10 simulation runs of 70,000 simulated decision epochs, from which we discard the first 15,000 decision epochs due to the warm-up effect. Table A.1 to Table A.6 in Appendix A.1 show the 95% confidence intervals of each instance of both the small and large test bed.

As a final note, since the overarching objective of this thesis is to develop scalable heuristics that perform well in practice, we discuss the results of the large test bed with networks of industrial size more extensively than the artificial network in our small test bed.

7.2.1 Small test bed

The results of the small symmetric test bed and the small asymmetric test bed are summarized in Table 7.5 and Table 7.6, respectively. In both tables, we present the minimum value, average value and maximum value of the GAP percents. We first distinguish between subsets of instances with the same value for a specific input parameter of Table 7.1 and Table 7.2, respectively, and subsequently present the results for all instances.

The main observations drawn from both tables can be summarized as follows:

- In the symmetric test bed, our most advanced heuristic, the DDDR-R heuristic, performs close to the optimal policy with an average GAP% of 4.6% and 10.4% at maximum. However, in the asymmetric test bed, which is rather pessimistic, we observe that the DDDR-R heuristic performs much worse with optimality gaps of 37.8% and 73.9%, respectively. Notwithstanding, the DDDR-R heuristic still outperforms the other heuristics. Additionally, if we compare the DDDR-R heuristic to the myopic SDSR heuristic (which has optimality gaps of 99.9% and 224.5%, respectively), we observe that the DDDR-R heuristic is still a huge improvement in the asymmetric test bed.
- In both test beds, the optimality gaps are relatively small on average when either a dynamic dispatching policy is employed or when reallocation is allowed in the policy. Hence, either including dynamic dispatching or reallocation are cost efficient and the combination of both using a dynamic dispatching policy and allowing for reallocation results in the smallest optimality gaps.
- In both test beds, for each of the eight heuristics, the range between the minimum gap and maximum gap are rather larger, indicating that the performance of the heuristics is not very robust to changing parameters. Nevertheless, the averages are more skewed to the minimum, suggesting that outliers (in terms of optimality gaps) occur sporadically. However, as this is the case with each of the eight heuristics in both test beds, we cannot say when this is exactly the case.
- In both test beds, for each of the four heuristics with the static repositioning heuristic, we observe that the increase of \hat{T} from 3 to 4 results in the highest increases in optimality gaps across the small test bed. A closer look at the optimal policy explains why this is the case. When $\hat{T} = 4$, the static repositioning heuristic determines that there is one dwell point, namely at the center of the network, whereas the optimal policy suggests different locations for the dwell points. By contrast, when $\hat{T} = 3$, the locations of the dwell points determined by the static repositioning heuristic coincide with the locations of the dwell points of the optimal policy. This observation highlights the importance of selecting good locations for dwell points.

Table 7.5: Summary of computational results for small symmetric test bed

(a) Heuristic 1-4

Parameter	Value	%GAP heuristic n											
		1			2			3			4		
		SDSR			SDSR-R			SDDR			SDDR-R		
		Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
λ_i $\forall i \in \mathcal{N}^d$	0.15	34.6	154.0	322.6	20.0	82.7	150.0	11.4	38.2	80.7	6.8	24.6	53.4
	0.20	35.1	114.1	224.1	20.5	65.0	118.2	13.3	41.2	82.0	7.5	26.4	55.4
	0.25	30.9	90.1	172.6	19.5	53.4	97.2	14.2	41.8	82.4	7.9	27.4	57.2
	0.30	26.6	74.2	139.9	18.5	45.6	84.1	14.1	40.8	78.3	7.8	27.3	57.5
	0.35	22.6	62.6	116.2	16.2	40.0	74.8	13.2	39.1	73.6	7.3	27.0	56.5
\hat{T}	3	22.6	32.6	42.8	16.2	21.8	32.9	11.4	16.6	20.8	6.8	9.1	11.4
	4	83.7	165.3	322.6	51.8	92.9	150.0	46.1	63.8	82.4	32.1	44.0	57.5
γ	0.50	22.6	103.6	322.6	16.2	58.2	150.0	11.5	42.6	82.4	6.9	28.2	57.5
	0.75	23.3	98.5	296.0	16.7	57.2	147.6	11.4	40.0	76.9	6.8	26.4	54.1
	1.00	26.1	94.8	276.1	17.4	56.6	143.0	11.7	37.9	71.4	7.2	25.0	50.8
(α_i, β_i) $\forall i \in \mathcal{N}^d$	(8,4)	22.6	89.7	258.5	16.2	54.0	135.8	11.4	33.6	61.2	6.8	21.8	39.7
	(8,6)	25.4	99.1	291.7	16.7	57.2	144.2	14.1	40.4	71.9	7.4	26.7	49.8
	(8,8)	27.0	108.3	322.6	17.0	60.8	150.0	15.7	46.6	82.4	8.0	31.2	57.5
Total		22.6	99.0	322.6	16.2	57.3	150.0	11.4	40.2	82.4	6.8	26.5	57.5

(b) Heuristic 5-8

Parameter	Value	%GAP heuristic n											
		5			6			7			8		
		DDSR			DDSR-R			DDDR			DDDR-R		
		Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
λ_i $\forall i \in \mathcal{N}^d$	0.15	27.3	136.3	283.6	14.8	63.6	107.2	8.6	27.4	55.4	1.9	5.2	10.4
	0.20	26.6	94.2	182.4	13.8	43.5	70.3	9.0	26.7	51.2	1.9	5.0	10.2
	0.25	22.9	69.2	126.7	11.5	31.1	49.4	9.1	24.4	44.3	1.9	4.6	9.0
	0.30	19.5	52.8	94.1	9.9	23.1	36.0	8.0	21.6	38.1	2.0	4.3	8.9
	0.35	16.2	41.5	71.9	7.9	17.6	27.5	7.1	18.8	32.0	1.7	4.1	8.3
\hat{T}	3	16.2	24.9	38.8	7.9	15.8	30.0	7.1	10.3	13.3	1.7	2.2	5.0
	4	60.1	132.7	283.6	22.5	55.7	107.2	25.5	37.3	55.4	4.0	7.0	10.4
γ	0.50	16.2	81.9	283.6	7.9	35.0	107.2	7.1	25.1	55.4	1.7	4.8	10.4
	0.75	16.7	78.5	262.0	8.4	35.7	105.5	7.1	23.6	50.4	1.9	4.6	9.8
	1.00	17.1	75.9	245.0	8.9	36.6	105.9	8.3	22.6	46.0	1.9	4.5	8.6
(α_i, β_i) $\forall i \in \mathcal{N}^d$	(8,4)	16.3	74.3	231.4	11.2	38.4	107.2	7.1	21.0	42.5	1.8	5.6	10.4
	(8,6)	16.4	78.6	257.9	9.3	35.4	105.0	8.7	23.7	49.9	1.9	4.4	8.7
	(8,8)	16.2	83.4	283.6	7.9	33.5	104.5	10.3	26.7	55.4	1.7	3.9	8.5
Total		16.2	78.8	283.6	7.9	35.8	107.2	7.1	23.8	55.4	1.7	4.6	10.4

Table 7.6: Summary of computational results for small asymmetric test bed

(a) Heuristic 1-4

Parameter	Value	%GAP heuristic n											
		1			2			3			4		
		SDSR			SDSR-R			SDDR			SDDR-R		
		Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
\hat{T}	3	30.5	44.7	73.7	21.1	32.6	52.8	27.8	39.1	61.1	20.7	31.8	50.3
	4	97.2	155.2	224.5	60.5	97.1	149.2	70.6	103.3	142.5	57.4	89.7	138.7
γ	0.50	30.5	105.9	224.5	22.6	66.8	149.2	27.8	73.1	142.5	22.1	62.2	138.7
	0.75	31.8	98.0	174.5	22.1	63.4	112.4	28.5	70.1	114.0	21.4	59.5	104.3
	1.00	32.0	95.9	194.5	21.1	64.4	132.3	28.4	70.3	126.7	20.7	60.5	123.0
(α_1, β_1)	(4,2)	41.1	112.4	224.5	30.9	75.9	149.2	37.5	80.3	142.5	30.9	71.5	138.7
	(8,4)	30.5	85.1	157.9	22.6	54.6	98.4	27.8	61.4	100.0	22.1	51.7	91.8
	(12,6)	32.5	98.1	203.9	22.7	62.3	117.5	28.5	67.8	118.1	21.4	57.8	106.9
	(20,10)	32.0	104.1	179.1	21.1	66.6	110.3	28.4	75.2	114.8	20.7	61.9	98.4
(α_i, β_i)	(8,4)	30.5	91.8	182.0	22.6	60.5	107.9	27.8	68.0	112.9	22.1	57.0	98.6
$\forall i \in$	(8,6)	32.5	99.1	176.8	22.7	64.1	112.4	28.5	70.7	114.0	21.4	60.1	104.3
$\{2, 3, 4\}$	(8,8)	32.0	108.9	224.5	21.1	69.9	149.2	28.4	74.8	142.5	20.7	65.2	138.7
Total		30.5	99.9	224.5	21.1	64.9	149.2	27.8	71.2	142.5	20.7	60.7	138.7

(b) Heuristic 5-8

Parameter	Value	%GAP heuristic n											
		5			6			7			8		
		DDSR			DDSR-R			DDDR			DDDR-R		
		Min	Avg	Max	Min	Avg	Max	Min	Avg	Max	Min	Avg	Max
\hat{T}	3	22.7	36.1	58.5	13.9	25.8	42.7	19.0	30.7	47.5	13.4	24.8	40.2
	4	73.4	122.4	183.1	35.7	59.4	86.9	46.9	72.8	101.7	31.2	50.8	73.9
γ	0.50	24.1	83.7	183.1	16.6	42.6	86.9	21.4	52.6	101.7	15.6	37.5	73.9
	0.75	24.3	77.3	141.4	15.3	41.3	70.6	20.2	50.7	82.9	14.7	36.6	60.8
	1.00	22.7	76.8	159.6	13.9	43.9	83.0	19.0	52.1	94.2	13.4	39.2	72.3
(α_1, β_1)	(4,2)	34.4	90.5	183.1	26.4	50.5	86.9	30.9	59.4	101.7	26.0	45.5	73.9
	(8,4)	24.1	65.1	116.9	16.6	32.9	54.0	21.4	42.2	66.4	15.4	29.2	46.1
	(12,6)	24.3	78.6	162.5	15.6	41.2	71.8	20.2	49.8	83.9	14.7	36.0	62.5
	(20,10)	22.7	82.9	144.0	13.9	45.8	71.4	19.0	55.7	82.9	13.4	40.5	58.8
(α_i, β_i)	(8,4)	24.1	75.2	154.7	17.5	43.8	74.9	21.4	52.0	86.8	16.8	39.6	65.8
$\forall i \in$	(8,6)	24.3	78.2	141.4	15.6	41.7	70.6	20.2	51.0	82.3	14.7	36.9	60.8
$\{2, 3, 4\}$	(8,8)	22.7	84.5	183.1	13.9	42.3	86.9	19.0	52.3	101.7	13.4	36.9	73.9
Total		22.7	79.3	183.1	13.9	42.6	86.9	19.0	51.8	101.7	13.4	37.8	73.9

7.2.2 Large test bed

The results of the large symmetric test bed and the large asymmetric test bed are summarized in Table 7.7 and Table 7.8, respectively. In both tables, we present the average values of the VAL percents, as calculated

by Equation (7.2). We first distinguish between subsets of instances with the same value for a specific input parameter of Table 7.3 and Table 7.4, respectively, and subsequently present the results for all instances.

Table 7.7: Summary of computational results for large symmetric test bed

Parameter	Value	Average %VAL heuristic n						
		2 SDSR-R	3 SDDR	4 SDDR-R	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
Number of demand nodes, $ \mathcal{N}^d $	100	31.1	-7.7	17.7	15.0	55.9	10.3	55.7
	180	32.2	1.3	29.6	28.2	66.9	31.7	68.0
Number of nodes, $ \mathcal{N} $	$(0.4 \cdot \mathcal{N}^d)^2$	35.4	-5.5	31.5	15.5	55.4	11.7	55.9
	$(0.6 \cdot \mathcal{N}^d)^2$	27.9	-0.9	15.7	27.7	67.5	30.3	67.9
Demand intensity, $\lambda_i, \forall i \in \mathcal{N}^d$	$U[0.001; 0.01]$	26.5	3.2	27.1	18.8	52.0	21.2	52.4
	$U[0.01; 0.05]$	36.8	-9.7	20.2	24.4	70.8	20.8	71.4
Number of service engineers, N	$\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$	20.0	0.2	6.0	34.5	72.1	37.3	71.5
	$\lfloor \frac{1}{5} \cdot \mathcal{N}^d \rfloor$	43.3	-6.6	41.2	8.7	50.7	4.7	52.3
Solution time threshold, \hat{T}	$\lfloor 1 \cdot \sqrt{\frac{ \mathcal{N} }{N}} \rfloor$	30.2	0.9	20.0	11.8	53.7	15.2	56.2
	$\lfloor 1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}} \rfloor$	33.1	-7.3	27.3	31.3	69.1	26.7	67.6
Travel cost, γ	1	32.2	-3.7	26.7	22.1	64.1	21.6	63.6
	4	31.1	-2.7	20.5	21.0	58.8	20.4	60.1
Cost penalty, $\alpha_i, \forall i \in \mathcal{N}^d$	50	30.1	3.6	24.9	20.9	59.2	26.4	60.8
	500	33.2	-10.0	22.4	22.3	63.6	15.5	63.0
Cost penalty, $\beta_i, \forall i \in \mathcal{N}^d$	$0.05 \cdot \alpha_i$	32.8	-4.4	20.8	30.0	67.7	29.9	68.0
	$0.1 \cdot \alpha_i$	30.5	-2.1	26.5	13.2	55.1	12.1	55.8
Total		31.7	-3.2	23.6	21.6	61.4	21.0	61.9

The main observations drawn from both tables can be summarized as follows:

- Huge savings can be obtained by either employing a dynamic dispatching policy or allowing for reallocation in the policy. The combination of both using a dynamic dispatching policy and allowing for reallocation results in the highest savings that can be attained, compared to the myopic SDSR policy, namely 61.4% and 61.9% for heuristic DDSR-R and DDDR-R, respectively, in the symmetric test bed and 58.1% and 60.1%, respectively, in the asymmetric test bed. This is a similar result we observed in the small test bed, where the optimality gaps of these heuristics were the smallest. Hence, our most advanced heuristic, the DDDR-R heuristic, outperforms all other heuristics on average across the large test bed.
- More specifically, allowing reallocation in the heuristic greatly outperforms heuristics where it is not allowed to reallocate. This can be seen when we directly compare the average %VAL of the heuristics where it is not allowed to reallocate with their reallocating counterpart. This observation triggered us to analyze the benefit of each aspect (dynamic dispatching, dynamic repositioning and reallocation) individually, which we discuss later in this section.

Table 7.8: Summary of computational results for large asymmetric test bed

Parameter	Value	Average %VAL heuristic n						
		2	3	4	5	6	7	8
		SDSR-R	SDDR	SDDR-R	DDSR	DDSR-R	DDDR	DDDR-R
Number of demand nodes, $ \mathcal{N}^d $	100	31.9	3.4	28.7	13.9	52.7	18.5	54.4
	180	30.7	6.6	29.9	26.7	63.4	34.9	65.8
Number of nodes, $ \mathcal{N} $	$(0.4 \cdot \mathcal{N}^d)^2$	33.8	4.6	34.6	14.8	52.2	20.5	54.6
	$(0.6 \cdot \mathcal{N}^d)^2$	28.8	5.4	24.0	25.8	63.9	32.8	65.6
Demand intensity, $\lambda_i, \forall i \in \mathcal{N}^d$	$U[0.001; 0.01]$	26.5	6.1	27.1	17.9	50.5	23.3	51.5
	$U[0.01; 0.05]$	36.1	3.9	31.5	22.8	65.6	30.1	68.7
Number of service engineers, N	$\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$	21.0	4.1	16.5	32.7	68.8	37.3	68.6
	$\lfloor \frac{1}{5} \cdot \mathcal{N}^d \rfloor$	41.6	6.0	42.1	8.0	47.3	16.0	51.7
Solution time threshold, \hat{T}	$\lfloor 1 \cdot \sqrt{\frac{ \mathcal{N} }{N}} \rfloor$	31.0	10.3	31.9	11.0	50.3	21.7	55.2
	$\lfloor 1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}} \rfloor$	31.6	-0.3	26.8	29.7	65.8	31.7	65.1
Travel cost, γ	1	33.6	5.1	30.2	21.7	61.6	28.3	62.8
	4	29.0	4.9	28.4	19.0	54.5	25.1	57.5
Cost penalty, $\alpha_i, \forall i \in \mathcal{N}^d$	$U[50; 100]$	29.7	9.1	27.8	19.3	54.6	29.6	57.9
	$U[100; 500]$	32.9	0.9	30.8	21.4	61.5	23.8	62.3
Cost penalty, $\beta_i, \forall i \in \mathcal{N}^d$	$0.05 \cdot \alpha_i$	32.9	5.1	30.5	28.1	64.3	34.8	66.6
	$0.1 \cdot \alpha_i$	29.7	4.9	28.1	12.6	51.8	18.6	53.6
Total		31.3	5.0	29.3	20.3	58.1	26.7	60.1

- In both the symmetric and asymmetric test bed, the results indicate that savings of all proposed heuristics (with the exception of heuristic SDSR-R and SDDR-R) tend to increase when networks become larger (both $|\mathcal{N}|$ and $|\mathcal{N}^d|$). These are promising results as our heuristics are in particular focused on network of large size.
- When considering either a dynamic dispatching heuristic or dynamic repositioning heuristic, we observe that only adopting a dynamic dispatching heuristic greatly outperforms only adopting a dynamic repositioning heuristic. With the SDDR heuristic savings of -3.2% (symmetric) to 5.0% (asymmetric) are attained, whereas with the DDSR heuristic savings of 20.3% (asymmetric) to 21.6% (symmetric) are attained. When allowing reallocation in the heuristic, this difference becomes even larger. With the SDDR-R heuristic savings of 23.6% (symmetric) to 29.3% (asymmetric) are attained, whereas with the DDSR-R heuristic huge savings of 58.1% (asymmetric) to 61.4% (symmetric) are attained. This is in contrast with findings in DAM literature, where it is shown that smarter allocation of idle ambulances to bases offers greater gains than advanced dispatching rules for ambulances to requests (Yue et al., 2012). This discrepancy could be explained by the different performance criterion. Whereas models in DAM literature are mainly focused on the minimization of late-arrivals (where an hour too late is considered equally as just a mere second too late), our objective is formulated in monetary terms where

penalty costs are incurred when a service engineer is already too late. In our case, dynamic dispatching rules, where the state of an equipment is taken into account, is then of more value than repositioning idle service engineers in anticipation of future demand. We come back to this observation when we discuss the substantial difference between the results of the small and large test bed with respect to the repositioning heuristic.

- Across all instances, savings tend to decrease for each of the four heuristics with the dynamic dispatching heuristic when the number of service engineers increases. This can be explained as follows. When the number of service engineers decreases, it is more likely that a demand node is located remotely from the nearest service engineer. Then, it could be the case that this demand node, upon failure, has to wait considerably long before eventually being served, thereby incurring penalty costs. Our proposed dynamic dispatching heuristic ensures that failed capital goods that are remotely located are also being served in a timely fashion. However, when the number of service engineers increases, it is less likely that a demand node is located remotely, thereby diminishing these effects. In other words, when each demand node is not too distant from the nearest idle service engineer, then our static dispatching heuristic suffices.

We also investigated the average relative distributions of the cost per time unit (i.e. which part is spent on α , β and γ). Note that these are relative fractions, which means that they do not say anything about the absolute values. The absolute values are displayed in Table 7.9 and Table 7.10, respectively. When observing Figures 7.1 and 7.2, where the average relative distribution of the cost per time unit is displayed for the symmetric and asymmetric test bed, respectively, we make two other observations:

- Employing the dynamic dispatching heuristic results in relatively lower penalty costs that are incurred after exceeding the solution time threshold, whereas employing the static counter part results in relatively lower traveling costs.
- Allowing reallocation amplifies the first observation.

Table 7.9: Distribution of average cost per time unit in euros for large symmetric test bed

	Heuristic	cost due to α	cost due to β	cost due to γ	total cost
1	SDSR	124.1	336.3	36.0	496.4
2	SDSR-R	78.8	268.7	27.0	374.5
3	SDDR	123.8	354.2	34.0	512.0
4	SDDR-R	83.3	304.7	25.8	413.8
5	DDSR	156.9	74.7	34.8	266.4
6	DDSR-R	74.6	12.5	23.9	111.0
7	DDDR	159.7	75.3	32.9	267.9
8	DDDR-R	78.0	13.3	22.3	113.6

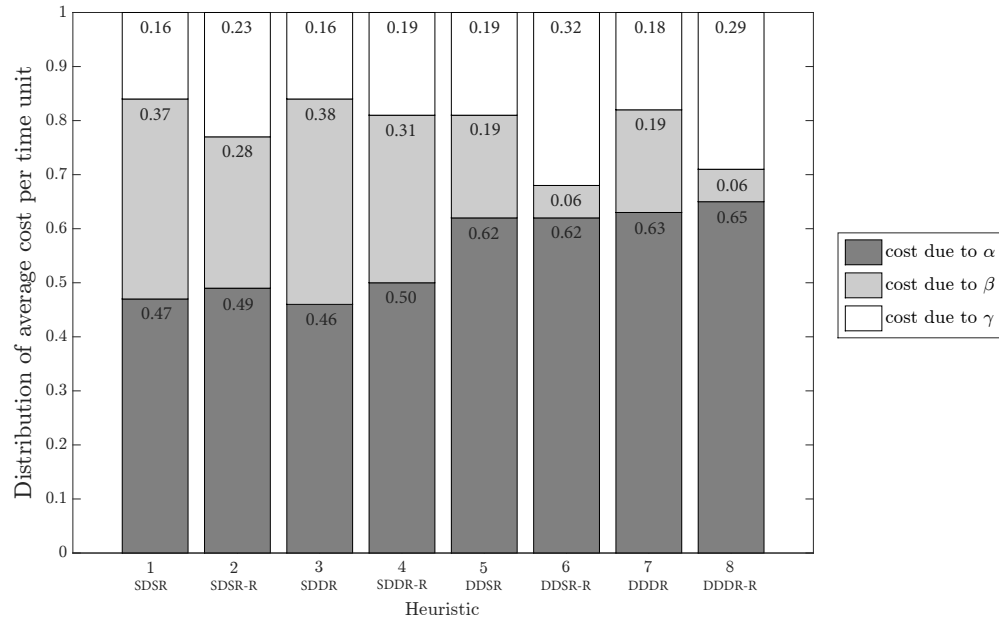


Figure 7.1: Distribution of average cost per time unit for large symmetric test bed

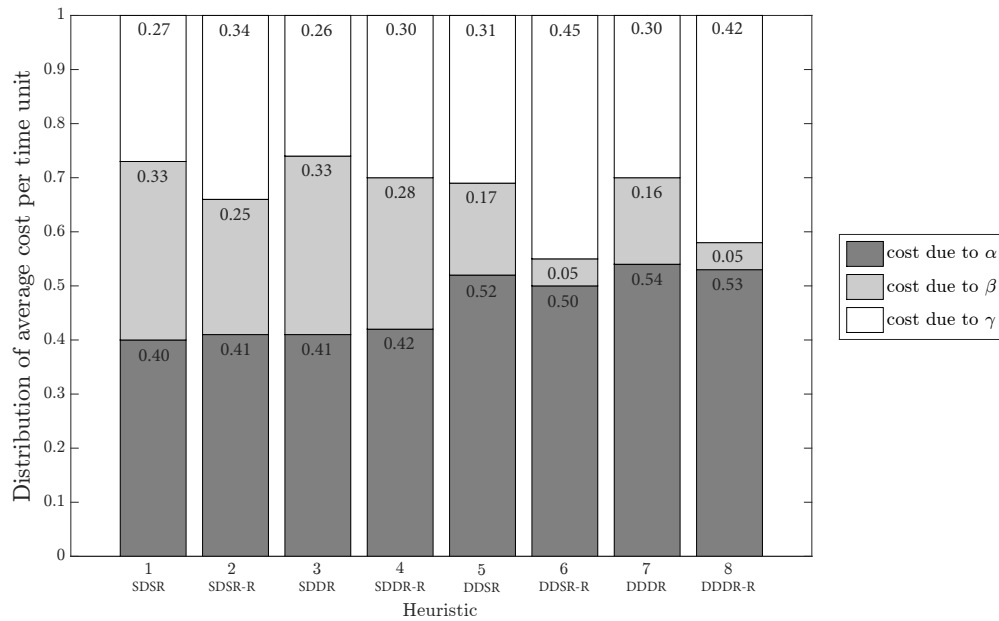


Figure 7.2: Distribution of average cost per time unit for large asymmetric test bed

These observations show the benefit of taking into account the state of equipment. Using a static dispatch policy (i.e. always sending the ‘closest-idle’ service engineer) indeed results in lower traveling costs, however it also results in that remote service requests have to wait too long before eventually being served, thereby incurring penalty costs. In contrast, our proposed dynamic dispatching heuristic ensures that failed capital goods that are remotely located are also being served in a timely fashion. Reallocation amplifies this effect

Table 7.10: Distribution of average cost per time unit in euros for large asymmetric test bed

	Heuristic	cost due to α	cost due to β	cost due to γ	total cost
1	SDSR	67.6	180.6	36.2	284.4
2	SDSR-R	43.1	143.3	27.1	213.5
3	SDDR	65.1	185.8	32.6	283.5
4	SDDR-R	44.7	160.2	25.3	230.2
5	DDSR	85.1	39.7	35.0	159.8
6	DDSR-R	40.5	6.6	24.1	71.2
7	DDDR	83.7	37.9	31.4	153.0
8	DDDR-R	42.5	7.3	21.9	71.5

since one can coordinate the dispatching decision at each decision epoch, resulting in that service requests that are on or close to the route to other service requests can be served, preventing them from incurring penalty costs.

Next, if we compare the results of the small test bed with the large test bed, we see one substantial difference. Whereas a heuristic that uses our dynamic repositioning heuristic greatly outperforms its counterpart with the static repositioning heuristic in the small test bed, this is not the case in the large test bed. This can be explained by the nature of our proposed dynamic repositioning heuristic. In our dynamic repositioning heuristic, we perform a local search for each idle service engineer where we calculate the weighted marginal coverage contribution of each neighboring node. In the small network of the small test bed, this calculation captures for each node the state of a large part of the whole network since most demand nodes can be reached within $\hat{T} - 1$ from each node. However, in the large network it can be the case that (a substantial part of all) demand nodes that are still up and running lie further away than $\hat{T} - 1$ from the nearest idle service engineer. If such a situation occurs, then such an area also remains uncovered due to the nature of our local search method. With our static repositioning heuristic, these areas will be covered as well, albeit without taking into account whether the demand nodes are actually up and running or not. Consequently, we can state that our static repositioning heuristic is already advanced enough for practical purposes. Note that a possible solution to this could be to first determine the distance to the nearest idle service engineer for each demand node and then take the maximum of these distances as the new value for $\hat{T} - 1$ in our local search.

Finally, we can quantify the benefit of either using the dynamic dispatching heuristic, dynamic repositioning heuristic or allowing reallocation in the policy by comparing each heuristic with its counterpart that differs on that one aspect and subsequently take the average of these four comparisons. To illustrate this, the benefit of allowing reallocation in the policy, denoted by $\%VAL^R$, is calculated as:

$$\%VAL^R = \frac{-100}{4} \cdot \left(\frac{g^2 - g^1}{g^1} + \frac{g^4 - g^3}{g^3} + \frac{g^6 - g^5}{g^5} + \frac{g^8 - g^7}{g^7} \right), \quad (7.3)$$

where g^n is as defined before. The benefit of either using the dynamic dispatching heuristic or dynamic repositioning heuristic, denoted by $\%VAL^{DD}$ and $\%VAL^{DR}$, respectively, are calculated analogously to

$\%VAL^R$. Hence, these benefits can be interpreted as savings that can be attained on average by either employing a dynamic instead of a static heuristic or by allowing reallocation (instead of not allowing) in the policy that is used. These savings are shown in Table 7.11.

Table 7.11: Benefit of either using the dynamic dispatching heuristic, dynamic repositioning heuristic or allowing reallocation in the policy

Benefit	Value
$\%VAL^R$	49.2
$\%VAL^{DD}$	27.7
$\%VAL^{DR}$	0.5

From Table 7.11 we observe that substantial savings of close to 50% can be attained by allowing reallocation in the policy. Current models, both in literature and in practice, limit themselves by imposing the constraint that once a decision has been made (either to dispatch or to reposition) the vehicle becomes eligible for a new decision once it has completed its service or has arrived at its final location. This quantification, which is currently lacking in the literature, shows that it is very beneficial to allow reallocation, regardless of the policy used, and can therefore be seen as an important contribution of this thesis. Table 7.11 also shows that significant savings, albeit it to a lesser degree, can be attained by employing the dynamic dispatching heuristic instead of the widely adopted ‘closest-idle first’-heuristic. Finally, Table 7.11 shows that employing the dynamic repositioning heuristic performs comparable to the static repositioning heuristic. We discussed the underlying argument for this before, where we extensively explained the substantial difference between the results of the small and large test bed.

Conclusion and discussion

We conclude this thesis by summarizing our main results, discussing and reflecting on the limitations of our research and pointing out opportunities for future research. We were the first to address the problem of real-time dispatching and repositioning of service engineers in a service logistics network to realize short solution times, such that costs (associated with exceeding the solution time threshold, delayed service requests and traveling of service engineers) are minimized. We formulated the problem as an Markov Decision Process (MDP) and solved the problem to optimality for a small network. We obtained insights into the structure of the optimal policy, along which we proposed two repositioning and two dispatching heuristics for both the reposition and dispatch sub-problem. In both cases we developed a static and dynamic heuristic. Our static heuristics are characterized by rules of thumbs that are determined a-priori and which are then always followed. By contrast, our dynamic heuristics are characterized by maximizing a goal function that takes into account information about the current state of the network. The developed dispatching (repositioning) heuristics are generic in the sense that they can be combined with any repositioning (dispatching) heuristic. We also analyzed the benefit of employing reallocation in the policy, i.e. being flexible in deviating from previous dispatch and reposition decisions.

8.1 Main results

We compared the performance of our proposed heuristics against the optimal policy in a small network in a small test bed and against a myopic policy, the SDSR heuristic (static dispatching heuristic, static repositioning heuristic, no reallocation), that is currently used in practice across a large test bed of industrial size. In the small test bed, we found that the average and the maximum optimality gap over all examined symmetric problem instances of the DDDR-R heuristic (dynamic dispatching heuristic, dynamic repositioning heuristic, reallocation), our most advanced heuristic, are 4.6% and 10.4%, respectively. This is a clear improvement compared to the myopic SDSR heuristic, which has optimality gaps of 99.0% and 322.6%,

respectively. However, in a rather pessimistic test bed, we found that the same DDDR-R heuristic performed worse with optimality gaps of 37.8% and 73.9%, respectively. Nevertheless, in the same test bed we observed that this was still a clear improvement compared to the myopic SDSR heuristic (optimality gaps of 99.9% and 224.5%, respectively). As the overarching objective of this thesis was to develop scalable heuristics that perform well in practice, we conducted a large test bed with networks of industrial size that we discussed more extensively than the artificial network in our small test bed. In this large test bed, we found that huge savings can be obtained by either employing a dynamic dispatching policy or allowing for reallocation in the policy. The combination of both using a dynamic dispatching policy and allowing for reallocation, where we observed savings of up to 61.9%, results in the highest savings in the real-life service logistics networks.

Furthermore, we quantified the benefit of individually using either a dynamic dispatching heuristic, a dynamic repositioning heuristic or allowing reallocation in the policy. We showed that savings of close to 50% can be attained by letting each service engineer be eligible for dispatch and reposition decisions, regardless of whether they are on their way to their destination or have already reached their destination. Current models, both in literature and in practice, limit themselves by imposing the constraint that once a decision has been made (either to dispatch or to reposition) the vehicle becomes eligible for a new decision once it has completed its service or has arrived at its final location. This quantification, which is currently lacking in the literature, shows that it is very beneficial from a cost-perspective to relax this limitation, regardless of the policy used, and can therefore be seen as an important result of this thesis. Employing the dynamic dispatching heuristic also results in high savings (27.7%) compared to the static counterpart, the widely adopted ‘closest-idle first’-heuristic, which tend to increase when the number of service engineers decreases (i.e. when the chance of remotely located demand nodes increases). Finally, we showed that employing the dynamic repositioning heuristic results in minimal savings (0.5%) compared to the static repositioning heuristic, which stem from the fact that areas that are uncovered, remain uncovered due to the nature of the local search method. At the same time, these minimal savings indicate that our static repositioning heuristic is already advanced enough for practical purposes.

Although our work is mainly motivated by the dispatch and reposition problem for service engineers in service logistics networks, it is also relevant for other logistics networks where dispatching and repositioning decisions have to be made in real-time. Results of our work are of particular interest to the area of emergency services management and the real-time management of taxis. The models that exist in the literature for the real-time management of emergency providers do not consider reallocation. However, we show that huge benefits can be gained from allowing reallocation in the dispatch and repositioning policies. In the real-time management of taxis, the central decision maker also faces a dispatching problem and reposition problem. Especially our proposed dynamic reposition heuristic can be easily adapted to the area of taxi management by translating the state of the equipment into the waiting time of a customer.

8.2 Reflection on limitations

The main, and at the same time most restrictive, assumption in our exact model is that we discretize both time and space in steps of Δt . This allowed us to model the problem as an exact MDP problem. However, as is often the case with higher dimensional MDPs, even this formulation was tractable only in oversimplified versions of the problem with few service engineers and small service logistics networks. Though this assumption oversimplified the problem, it helped us to gain insights into the optimal policy with respect to three aspects, i.e. location strategy for idle service engineers, dispatching strategy of service engineers that takes into account the state of the system, and reallocation of service engineers. Note that these insights are solely focused on the movements of service engineers. Likewise, our proposed heuristics are also solely focused on the movements of service engineers, irrespective of the duration of repairs or even travel times. Our aim was to use as little information possible, such that the heuristics scale well in practice, and such that it is implicitly insensitive to choices of the parameters. As a result, the proposed heuristics do not depend on Δt but they only need as input where idle service engineers are located, their (expected) travel times to each demand node, and, if applicable, the arrival times of service requests. Additionally, when reallocation is allowed in the policy, managers of service organizations only have to choose how often previous dispatch and reposition decision should be reconsidered.

We can thus state that our exact model is limited by our assumption with regard to Δt , but that this assumption has not restricted us from reaching the overarching goal of this thesis, i.e. developing scalable heuristics that perform well in practice.

8.3 Future research

Suggestions for future research are twofold. First, our research can be extended by looking into the limitations of this study. In the formulation of our exact model we have assumed that i) travel times are deterministic, ii) repair times are deterministic and can only take one certain value (Δt) irrespective of the type of the repair, iii) service engineers are indistinguishable and iv) there is only one solution time threshold for all customers. From a practical point of view, these assumptions do not always hold. Hence, future research can focus on relaxing one or more of these assumptions in the exact model. With respect to the second limitation, we already shortly discussed how deterministic repair times that are an integral multiple of Δt can be incorporated. In contrast to the exact model, the first two limitations do not apply to both our dispatching and repositioning heuristics since they do not rely on these assumptions (as discussed in the previous section). With regards to assumption iv), our dynamic dispatching and both repositioning heuristics could incorporate different solution time thresholds by means of a weight factor.

Second, we suggest to investigate research question 1 and research question 2 that we discussed in Chapter 1, which were related to how many service engineers are needed and how many and which spare parts should be stored in the local warehouse, respectively. With this research we made a starting point for analyzing our proposed innovative network design by developing scalable heuristics that assist decision makers in answering question 3 under given choices for research question 1 and independent from research question 2. This leaves research question 1 and research question 2 open for further research. Answering all three research questions will complete the analysis, planning and control of our proposed innovative network. The performance of this network can then be compared to the performance of traditional service logistics networks. Such a comparison should be done under a wide range of conditions, but in particular for a continuum of solution time targets. Managers of service organizations can then base their choice for the service logistics network design on the solution time target that they need to attain.

The spare parts problem of research question 2 in isolation falls in the class of multi-item, single-location inventory models that are subjected to an aggregate fill-rate constraint (which is the service measure). A single-item version of this model was initially formulated by Feeney and Sherbrooke (1966), which is later extended to a multi-item formulation (see Sherbrooke (2006), chapter 2). Several exact optimization methods have been proposed to determine optimal base-stock levels for this problem (see Van Houtum and Kranenburg (2015), chapter 2), which could be used in this research. One difficulty that arises here is that by decomposing the spare parts problem and the dispatching and repositioning problem into two sub-problems, it is implicitly assumed that both problems are independent. However, in practice this will not be the case as both the service engineer and the spare part need to be at the same place at exactly the same time, which means that they are dependent on each other.

Next, the trade-off between higher coverage and the costs of additional service engineers on the overall performance should be studied (e.g., by means of enumeration). Integrating all decisions at each layer and evaluating the performance of our proposed network design is a difficult problem that is likely to be intractable using analytical methods. Instead, Simulation-Based Optimization (SBO), which is a way to solve problems of high computational complexity, could be a promising technique to tackle this problem. Ghosh et al. (2013) propose to use SBO for complex problems in two parts. First, a tractable analytical model is solved in order to provide good solutions for the individual decisions. In our case, this will be for decision 2 and the decision that was under study in this thesis. This solution is then used as input for a simulation model, which can be solved using local search methods. This approach was refined recently by Dieker et al. (2016), who use an iterative method between the two stages.

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APPENDIX A

Additional information computational study

A.1 Confidence intervals computational study

Table A.1: Average cost per time unit and 95% confidence interval for each instance of small symmetric test bed

Instance $\{\lambda, \hat{T}, \gamma, (\alpha, \beta)\}$	Average cost per time unit and 95% confidence interval of heuristic n							
	1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
1 {0.15,3,0.5,(8,4)}	5.28 ± 0.0103	4.90 ± 0.0108	4.21 ± 0.0094	4.04 ± 0.0098	5.12 ± 0.0102	4.79 ± 0.0107	4.10 ± 0.0092	3.86 ± 0.0096
2 {0.2,3,0.5,(8,4)}	6.67 ± 0.0108	6.20 ± 0.0114	5.57 ± 0.0102	5.28 ± 0.0107	6.39 ± 0.0108	6.00 ± 0.0113	5.36 ± 0.0101	5.04 ± 0.0105
3 {0.25,3,0.5,(8,4)}	7.80 ± 0.0110	7.30 ± 0.0117	6.81 ± 0.0107	6.45 ± 0.0112	7.44 ± 0.0110	7.03 ± 0.0116	6.51 ± 0.0105	6.11 ± 0.0110
4 {0.3,3,0.5,(8,4)}	8.74 ± 0.0110	8.22 ± 0.0117	7.87 ± 0.0109	7.44 ± 0.0114	8.31 ± 0.0111	7.88 ± 0.0117	7.46 ± 0.0107	7.05 ± 0.0112
5 {0.35,3,0.5,(8,4)}	9.48 ± 0.0110	8.99 ± 0.0117	8.75 ± 0.0109	8.30 ± 0.0114	8.99 ± 0.0111	8.60 ± 0.0117	8.28 ± 0.0108	7.87 ± 0.0113
6 {0.15,4,0.5,(8,4)}	3.01 ± 0.0070	1.98 ± 0.0068	1.33 ± 0.0058	1.16 ± 0.0055	2.78 ± 0.0065	1.74 ± 0.0061	1.20 ± 0.0053	0.93 ± 0.0048
7 {0.2,4,0.5,(8,4)}	3.70 ± 0.0082	2.61 ± 0.0078	2.11 ± 0.0073	1.83 ± 0.0069	3.32 ± 0.0075	2.22 ± 0.0070	1.85 ± 0.0066	1.45 ± 0.0060
8 {0.25,4,0.5,(8,4)}	4.33 ± 0.0089	3.23 ± 0.0086	2.90 ± 0.0083	2.54 ± 0.0080	3.81 ± 0.0082	2.68 ± 0.0077	2.47 ± 0.0075	1.98 ± 0.0071
9 {0.3,4,0.5,(8,4)}	4.90 ± 0.0095	3.82 ± 0.0092	3.65 ± 0.0091	3.21 ± 0.0088	4.25 ± 0.0087	3.14 ± 0.0083	3.07 ± 0.0082	2.54 ± 0.0079
10 {0.35,4,0.5,(8,4)}	5.40 ± 0.0098	4.34 ± 0.0096	4.35 ± 0.0096	3.87 ± 0.0093	4.64 ± 0.0090	3.56 ± 0.0088	3.61 ± 0.0087	3.06 ± 0.0085
11 {0.15,3,0.75,(8,4)}	5.53 ± 0.0103	5.15 ± 0.0110	4.35 ± 0.0094	4.17 ± 0.0101	5.36 ± 0.0102	5.02 ± 0.0109	4.26 ± 0.0093	4.00 ± 0.0099
12 {0.2,3,0.75,(8,4)}	6.97 ± 0.0108	6.47 ± 0.0116	5.79 ± 0.0103	5.48 ± 0.0110	6.70 ± 0.0107	6.26 ± 0.0115	5.57 ± 0.0101	5.21 ± 0.0108
13 {0.25,3,0.75,(8,4)}	8.13 ± 0.0110	7.62 ± 0.0119	7.04 ± 0.0108	6.65 ± 0.0114	7.76 ± 0.0109	7.31 ± 0.0118	6.73 ± 0.0106	6.30 ± 0.0113
14 {0.3,3,0.75,(8,4)}	9.06 ± 0.0110	8.55 ± 0.0119	8.13 ± 0.0109	7.70 ± 0.0117	8.63 ± 0.0110	8.19 ± 0.0119	7.70 ± 0.0108	7.30 ± 0.0115
15 {0.35,3,0.75,(8,4)}	9.83 ± 0.0109	9.31 ± 0.0119	9.08 ± 0.0109	8.59 ± 0.0117	9.33 ± 0.0110	8.92 ± 0.0119	8.54 ± 0.0108	8.14 ± 0.0116
16 {0.15,4,0.75,(8,4)}	3.29 ± 0.0071	2.26 ± 0.0069	1.49 ± 0.0059	1.31 ± 0.0057	3.08 ± 0.0066	2.01 ± 0.0063	1.35 ± 0.0054	1.07 ± 0.0049
17 {0.2,4,0.75,(8,4)}	4.01 ± 0.0082	2.93 ± 0.0080	2.30 ± 0.0074	2.02 ± 0.0071	3.64 ± 0.0075	2.52 ± 0.0071	2.03 ± 0.0067	1.62 ± 0.0062
18 {0.25,4,0.75,(8,4)}	4.66 ± 0.0089	3.55 ± 0.0087	3.15 ± 0.0085	2.75 ± 0.0082	4.15 ± 0.0082	3.00 ± 0.0079	2.70 ± 0.0076	2.20 ± 0.0072
19 {0.3,4,0.75,(8,4)}	5.25 ± 0.0094	4.13 ± 0.0093	3.93 ± 0.0092	3.47 ± 0.0090	4.59 ± 0.0086	3.46 ± 0.0085	3.33 ± 0.0083	2.76 ± 0.0080
20 {0.35,4,0.75,(8,4)}	5.75 ± 0.0097	4.69 ± 0.0097	4.64 ± 0.0097	4.15 ± 0.0095	4.97 ± 0.0089	3.90 ± 0.0090	3.90 ± 0.0087	3.33 ± 0.0087
21 {0.15,3,1,(8,4)}	5.77 ± 0.0103	5.38 ± 0.0113	4.52 ± 0.0096	4.33 ± 0.0104	5.61 ± 0.0102	5.25 ± 0.0112	4.39 ± 0.0094	4.13 ± 0.0102
22 {0.2,3,1,(8,4)}	7.27 ± 0.0108	6.75 ± 0.0118	5.97 ± 0.0104	5.68 ± 0.0113	6.98 ± 0.0107	6.54 ± 0.0118	5.75 ± 0.0103	5.40 ± 0.0111
23 {0.25,3,1,(8,4)}	8.45 ± 0.0110	7.90 ± 0.0121	7.29 ± 0.0109	6.89 ± 0.0118	8.07 ± 0.0109	7.61 ± 0.0120	6.94 ± 0.0107	6.53 ± 0.0116
24 {0.3,3,1,(8,4)}	9.40 ± 0.0110	8.86 ± 0.0121	8.39 ± 0.0110	7.96 ± 0.0119	8.95 ± 0.0110	8.50 ± 0.0121	7.97 ± 0.0109	7.53 ± 0.0118
25 {0.35,3,1,(8,4)}	10.15 ± 0.0109	9.64 ± 0.0120	9.35 ± 0.0110	8.86 ± 0.0119	9.65 ± 0.0109	9.24 ± 0.0121	8.81 ± 0.0109	8.40 ± 0.0118
26 {0.15,4,1,(8,4)}	3.59 ± 0.0072	2.54 ± 0.0071	1.63 ± 0.0061	1.47 ± 0.0060	3.36 ± 0.0068	2.29 ± 0.0065	1.50 ± 0.0057	1.21 ± 0.0051
27 {0.2,4,1,(8,4)}	4.35 ± 0.0083	3.24 ± 0.0081	2.50 ± 0.0076	2.21 ± 0.0074	3.96 ± 0.0076	2.82 ± 0.0073	2.23 ± 0.0069	1.79 ± 0.0064
28 {0.25,4,1,(8,4)}	5.00 ± 0.0090	3.88 ± 0.0089	3.39 ± 0.0087	2.98 ± 0.0084	4.49 ± 0.0083	3.33 ± 0.0080	2.93 ± 0.0078	2.40 ± 0.0074
29 {0.3,4,1,(8,4)}	5.60 ± 0.0095	4.49 ± 0.0095	4.20 ± 0.0093	3.72 ± 0.0092	4.93 ± 0.0087	3.79 ± 0.0087	3.59 ± 0.0084	3.00 ± 0.0082

Continued on next page

Table A.1: – continued from previous page

Average cost per time unit and 95% confidence interval of heuristic n								
Instance $\{\lambda, \bar{T}, \gamma, (\alpha, \beta)\}$	1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
30 {0.35,4,1,(8,4)}	6.10 ± 0.0098	5.04 ± 0.0099	4.92 ± 0.0098	4.41 ± 0.0097	5.31 ± 0.0089	4.23 ± 0.0092	4.17 ± 0.0088	3.57 ± 0.0089
31 {0.15,3,0.5,(8,6)}	6.10 ± 0.0116	5.52 ± 0.0118	5.08 ± 0.0110	4.81 ± 0.0112	5.82 ± 0.0113	5.36 ± 0.0115	4.90 ± 0.0107	4.56 ± 0.0109
32 {0.2,3,0.5,(8,6)}	7.93 ± 0.0124	7.18 ± 0.0127	6.85 ± 0.0121	6.35 ± 0.0123	7.48 ± 0.0120	6.86 ± 0.0123	6.50 ± 0.0117	5.98 ± 0.0119
33 {0.25,3,0.5,(8,6)}	9.45 ± 0.0127	8.63 ± 0.0131	8.43 ± 0.0127	7.82 ± 0.0129	8.85 ± 0.0123	8.16 ± 0.0127	7.91 ± 0.0122	7.28 ± 0.0124
34 {0.3,3,0.5,(8,6)}	10.70 ± 0.0128	9.89 ± 0.0133	9.84 ± 0.0129	9.14 ± 0.0132	9.97 ± 0.0124	9.27 ± 0.0129	9.18 ± 0.0124	8.48 ± 0.0127
35 {0.35,3,0.5,(8,6)}	11.75 ± 0.0126	10.94 ± 0.0132	11.02 ± 0.0129	10.28 ± 0.0133	10.91 ± 0.0123	10.25 ± 0.0129	10.21 ± 0.0124	9.55 ± 0.0128
36 {0.15,4,0.5,(8,6)}	3.46 ± 0.0078	2.15 ± 0.0074	1.50 ± 0.0065	1.29 ± 0.0062	3.16 ± 0.0072	1.81 ± 0.0064	1.32 ± 0.0058	0.96 ± 0.0049
37 {0.2,4,0.5,(8,6)}	4.24 ± 0.0091	2.92 ± 0.0087	2.40 ± 0.0082	2.07 ± 0.0078	3.75 ± 0.0082	2.33 ± 0.0073	2.04 ± 0.0072	1.51 ± 0.0063
38 {0.25,4,0.5,(8,6)}	5.01 ± 0.0100	3.68 ± 0.0097	3.34 ± 0.0095	2.94 ± 0.0092	4.30 ± 0.0089	2.86 ± 0.0081	2.75 ± 0.0082	2.10 ± 0.0074
39 {0.3,4,0.5,(8,6)}	5.71 ± 0.0107	4.42 ± 0.0105	4.30 ± 0.0105	3.77 ± 0.0101	4.76 ± 0.0094	3.36 ± 0.0088	3.42 ± 0.0090	2.70 ± 0.0083
40 {0.35,4,0.5,(8,6)}	6.33 ± 0.0111	5.12 ± 0.0110	5.09 ± 0.0110	4.57 ± 0.0110	5.20 ± 0.0098	3.84 ± 0.0093	4.01 ± 0.0094	3.28 ± 0.0089
41 {0.15,3,0.75,(8,6)}	6.33 ± 0.0116	5.77 ± 0.0120	5.24 ± 0.0110	4.92 ± 0.0115	6.06 ± 0.0112	5.57 ± 0.0118	5.08 ± 0.0108	4.69 ± 0.0112
42 {0.2,3,0.75,(8,6)}	8.22 ± 0.0124	7.47 ± 0.0129	7.02 ± 0.0122	6.54 ± 0.0126	7.78 ± 0.0120	7.12 ± 0.0125	6.70 ± 0.0118	6.15 ± 0.0122
43 {0.25,3,0.75,(8,6)}	9.75 ± 0.0126	8.94 ± 0.0133	8.64 ± 0.0127	8.05 ± 0.0133	9.14 ± 0.0122	8.44 ± 0.0129	8.14 ± 0.0123	7.51 ± 0.0127
44 {0.3,3,0.75,(8,6)}	11.04 ± 0.0127	10.22 ± 0.0134	10.08 ± 0.0130	9.38 ± 0.0135	10.29 ± 0.0123	9.58 ± 0.0130	9.39 ± 0.0125	8.72 ± 0.0130
45 {0.35,3,0.75,(8,6)}	12.08 ± 0.0125	11.26 ± 0.0134	11.31 ± 0.0129	10.55 ± 0.0135	11.23 ± 0.0122	10.57 ± 0.0130	10.46 ± 0.0125	9.80 ± 0.0130
46 {0.15,4,0.75,(8,6)}	3.75 ± 0.0079	2.43 ± 0.0076	1.66 ± 0.0066	1.45 ± 0.0064	3.45 ± 0.0072	2.09 ± 0.0065	1.47 ± 0.0059	1.10 ± 0.0051
47 {0.2,4,0.75,(8,6)}	4.58 ± 0.0091	3.24 ± 0.0089	2.60 ± 0.0083	2.28 ± 0.0081	4.07 ± 0.0082	2.64 ± 0.0075	2.23 ± 0.0073	1.68 ± 0.0064
48 {0.25,4,0.75,(8,6)}	5.36 ± 0.0100	4.00 ± 0.0098	3.60 ± 0.0096	3.14 ± 0.0094	4.63 ± 0.0089	3.18 ± 0.0083	2.98 ± 0.0083	2.32 ± 0.0076
49 {0.3,4,0.75,(8,6)}	6.05 ± 0.0106	4.75 ± 0.0106	4.53 ± 0.0105	4.00 ± 0.0103	5.11 ± 0.0093	3.70 ± 0.0090	3.67 ± 0.0090	2.93 ± 0.0084
50 {0.35,4,0.75,(8,6)}	6.68 ± 0.0110	5.46 ± 0.0111	5.39 ± 0.0111	4.83 ± 0.0110	5.56 ± 0.0097	4.17 ± 0.0095	4.30 ± 0.0095	3.54 ± 0.0091
51 {0.15,3,1,(8,6)}	6.61 ± 0.0116	6.00 ± 0.0123	5.39 ± 0.0111	5.08 ± 0.0119	6.34 ± 0.0113	5.81 ± 0.0120	5.23 ± 0.0109	4.83 ± 0.0115
52 {0.2,3,1,(8,6)}	8.53 ± 0.0124	7.74 ± 0.0131	7.23 ± 0.0123	6.74 ± 0.0130	8.04 ± 0.0119	7.39 ± 0.0128	6.89 ± 0.0119	6.34 ± 0.0125
53 {0.25,3,1,(8,6)}	10.06 ± 0.0126	9.22 ± 0.0135	8.90 ± 0.0129	8.26 ± 0.0136	9.46 ± 0.0122	8.74 ± 0.0131	8.38 ± 0.0124	7.71 ± 0.0130
54 {0.3,3,1,(8,6)}	11.38 ± 0.0126	10.50 ± 0.0137	10.36 ± 0.0130	9.63 ± 0.0138	10.61 ± 0.0122	9.91 ± 0.0132	9.65 ± 0.0125	8.97 ± 0.0133
55 {0.35,3,1,(8,6)}	12.44 ± 0.0125	11.58 ± 0.0136	11.58 ± 0.0130	10.82 ± 0.0138	11.58 ± 0.0121	10.88 ± 0.0132	10.76 ± 0.0125	10.06 ± 0.0133
56 {0.15,4,1,(8,6)}	4.05 ± 0.0080	2.72 ± 0.0077	1.80 ± 0.0068	1.58 ± 0.0065	3.74 ± 0.0073	2.36 ± 0.0067	1.61 ± 0.0061	1.24 ± 0.0053
57 {0.2,4,1,(8,6)}	4.90 ± 0.0092	3.54 ± 0.0090	2.80 ± 0.0085	2.45 ± 0.0082	4.37 ± 0.0082	2.95 ± 0.0077	2.42 ± 0.0075	1.86 ± 0.0066
58 {0.25,4,1,(8,6)}	5.69 ± 0.0101	4.35 ± 0.0100	3.82 ± 0.0098	3.37 ± 0.0096	4.96 ± 0.0089	3.48 ± 0.0084	3.23 ± 0.0085	2.52 ± 0.0077
59 {0.3,4,1,(8,6)}	6.40 ± 0.0106	5.09 ± 0.0107	4.79 ± 0.0106	4.26 ± 0.0105	5.47 ± 0.0094	4.02 ± 0.0091	3.94 ± 0.0091	3.16 ± 0.0086
60 {0.35,4,1,(8,6)}	7.03 ± 0.0110	5.80 ± 0.0113	5.68 ± 0.0112	5.09 ± 0.0112	5.88 ± 0.0096	4.51 ± 0.0097	4.57 ± 0.0096	3.79 ± 0.0093
61 {0.15,3,0.5,(8,8)}	6.91 ± 0.0133	6.15 ± 0.0131	5.94 ± 0.0129	5.56 ± 0.0129	6.53 ± 0.0127	5.89 ± 0.0126	5.74 ± 0.0124	5.23 ± 0.0123
62 {0.2,3,0.5,(8,8)}	9.15 ± 0.0145	8.16 ± 0.0144	8.06 ± 0.0143	7.42 ± 0.0143	8.57 ± 0.0137	7.71 ± 0.0137	7.63 ± 0.0137	6.90 ± 0.0135
63 {0.25,3,0.5,(8,8)}	11.08 ± 0.0150	9.94 ± 0.0150	10.01 ± 0.0151	9.21 ± 0.0151	10.22 ± 0.0141	9.27 ± 0.0142	9.37 ± 0.0144	8.47 ± 0.0142
64 {0.3,3,0.5,(8,8)}	12.71 ± 0.0151	11.54 ± 0.0153	11.72 ± 0.0155	10.84 ± 0.0155	11.63 ± 0.0143	10.70 ± 0.0145	10.87 ± 0.0146	9.94 ± 0.0146
65 {0.35,3,0.5,(8,8)}	13.99 ± 0.0150	12.88 ± 0.0154	13.26 ± 0.0154	12.22 ± 0.0156	12.80 ± 0.0142	11.89 ± 0.0145	12.15 ± 0.0146	11.21 ± 0.0146
66 {0.15,4,0.5,(8,8)}	3.90 ± 0.0089	2.30 ± 0.0081	1.67 ± 0.0074	1.41 ± 0.0069	3.54 ± 0.0080	1.89 ± 0.0067	1.43 ± 0.0064	1.00 ± 0.0052
67 {0.2,4,0.5,(8,8)}	4.79 ± 0.0104	3.22 ± 0.0098	2.69 ± 0.0094	2.30 ± 0.0088	4.17 ± 0.0091	2.45 ± 0.0078	2.23 ± 0.0080	1.58 ± 0.0066
68 {0.25,4,0.5,(8,8)}	5.71 ± 0.0115	4.13 ± 0.0111	3.82 ± 0.0110	3.29 ± 0.0105	4.75 ± 0.0099	3.02 ± 0.0087	3.02 ± 0.0091	2.22 ± 0.0078
69 {0.3,4,0.5,(8,8)}	6.55 ± 0.0123	5.03 ± 0.0121	4.87 ± 0.0121	4.30 ± 0.0117	5.30 ± 0.0104	3.58 ± 0.0094	3.77 ± 0.0099	2.88 ± 0.0088
70 {0.35,4,0.5,(8,8)}	7.26 ± 0.0129	5.87 ± 0.0128	5.84 ± 0.0128	5.26 ± 0.0125	5.78 ± 0.0108	4.12 ± 0.0100	4.44 ± 0.0105	3.49 ± 0.0095
71 {0.15,3,0.75,(8,8)}	7.17 ± 0.0133	6.39 ± 0.0134	6.11 ± 0.0129	5.68 ± 0.0132	6.78 ± 0.0127	6.13 ± 0.0129	5.90 ± 0.0125	5.37 ± 0.0126
72 {0.2,3,0.75,(8,8)}	9.48 ± 0.0145	8.44 ± 0.0146	8.24 ± 0.0143	7.65 ± 0.0147	8.81 ± 0.0137	7.97 ± 0.0139	7.82 ± 0.0137	7.11 ± 0.0139
73 {0.25,3,0.75,(8,8)}	11.43 ± 0.0150	10.25 ± 0.0153	10.26 ± 0.0152	9.43 ± 0.0155	10.54 ± 0.0141	9.58 ± 0.0144	9.59 ± 0.0144	8.69 ± 0.0145
74 {0.3,3,0.75,(8,8)}	13.03 ± 0.0150	11.85 ± 0.0155	12.03 ± 0.0155	11.06 ± 0.0158	11.96 ± 0.0142	11.00 ± 0.0147	11.12 ± 0.0146	10.17 ± 0.0148
75 {0.35,3,0.75,(8,8)}	14.36 ± 0.0149	13.23 ± 0.0155	13.55 ± 0.0154	12.52 ± 0.0159	13.14 ± 0.0141	12.21 ± 0.0147	12.42 ± 0.0146	11.48 ± 0.0149
76 {0.15,4,0.75,(8,8)}	4.19 ± 0.0089	2.62 ± 0.0084	1.82 ± 0.0075	1.57 ± 0.0071	3.83 ± 0.0080	2.16 ± 0.0069	1.59 ± 0.0066	1.13 ± 0.0053
77 {0.2,4,0.75,(8,8)}	5.12 ± 0.0104	3.52 ± 0.0099	2.92 ± 0.0095	2.50 ± 0.0091	4.48 ± 0.0091	2.75 ± 0.0079	2.43 ± 0.0081	1.76 ± 0.0068
78 {0.25,4,0.75,(8,8)}	6.02 ± 0.0115	4.46 ± 0.0112	4.01 ± 0.0110	3.52 ± 0.0107	5.09 ± 0.0098	3.35 ± 0.0088	3.26 ± 0.0092	2.43 ± 0.0080
79 {0.3,4,0.75,(8,8)}	6.87 ± 0.0122	5.33 ± 0.0122	5.15 ± 0.0121	4.54 ± 0.0119	5.63 ± 0.0104	3.91 ± 0.0096	4.02 ± 0.0100	3.10 ± 0.0090
80 {0.35,4,0.75,(8,8)}	7.62 ± 0.0128	6.22 ± 0.0129	6.13 ± 0.0129	5.56 ± 0.0128	6.12 ± 0.0107	4.46 ± 0.0102	4.72 ± 0.0105	3.76 ± 0.0097
81 {0.15,3,1,(8,8)}	7.43 ± 0.0133	6.61 ± 0.0137	6.26 ± 0.0130	5.84 ± 0.0136	7.01 ± 0.0127	6.35 ± 0.0131	6.04 ± 0.0126	5.50 ± 0.0130
82 {0.2,3,1,(8,8)}	9.74 ± 0.0144	8.70 ± 0.0149	8.51 ± 0.0145	7.83 ± 0.0150	9.11 ± 0.0136	8.23 ± 0.0141	8.06 ± 0.0139	7.26 ± 0.0142
83 {0.25,3,1,(8,8)}	11.73 ± 0.0149	10.56 ± 0.0155	10.49 ± 0.0153	9.67 ± 0.0158	10.84 ± 0.0140	9.85 ± 0.0147	9.83 ± 0.0145	8.93 ± 0.0148
84 {0.3,3,1,(8,8)}	13.38 ± 0.0149	12.18 ± 0.0158	12.28 ± 0.0155	11.29 ± 0.0161	12.26 ± 0.0141	11.31 ± 0.0149	11.38 ± 0.0147	10.39 ± 0.0151
85 {0.35,3,1,(8,8)}	14.72 ± 0.0148	13.53 ± 0.0158	13.82 ± 0.0155	12.79 ± 0.0162	13.48 ± 0.0139	12.53 ± 0.0149	12.69 ± 0.0146	11.72 ± 0.0152
86 {0.15,4,1,(8,8)}	4.50 ± 0.0090	2.91 ± 0.0085	1.97 ± 0.0076	1.71 ± 0.0073	4.13 ± 0.0081	2.44 ± 0.0070	1.75 ± 0.0067	1.28 ± 0.0055
87 {0.2,4,1,(8,8)}	5.46 ± 0.0104	3.84 ± 0.0101	3.10 ± 0.0096	2.68 ± 0.0093	4.80 ± 0.0091	3.07 ± 0.0081	2.62 ± 0.0082	1.93 ± 0.0070
88 {0.25,4,1,(8,8)}	6.37 ± 0.0115	4.79 ± 0.0114	4.28 ± 0.0112	3.75 ± 0.0109	5.42 ± 0.0098	3.67 ± 0.0090	3.49 ± 0.0093	2.63 ± 0.0082
89 {0.3,4,1,(8,8)}	7.23 ± 0.0122	5.69 ± 0.0123	5.41 ± 0.0122	4.80 ± 0.0121	5.97 ± 0.0103	4.24 ± 0.0097	4.29 ± 0.0101	3.34 ± 0.0091
90 {0.35,4,1,(8,8)}	7.99 ± 0.0127	6.55 ± 0.0130	6.43 ± 0.0130	5.80 ± 0.0129	6.47 ± 0.0107	4.78 ± 0.0103	4.98 ± 0.0106	4.02 ± 0.0099

Table A.2: Average cost per time unit and 95% confidence interval for each instance of small asymmetric test bed

Instance $\{\bar{T}, \gamma, (\alpha_1, \beta_1), (\alpha_i, \beta_i)\}$	Average cost per time unit and 95% confidence interval of heuristic n							
	1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
1 {3,0.5,(4,2),(8,4)}	6.09 ± 0.0101	5.66 ± 0.0107	6.02 ± 0.0100	5.76 ± 0.0106	5.82 ± 0.0100	5.49 ± 0.0106	5.78 ± 0.0100	5.54 ± 0.0105
2 {4,0.5,(4,2),(8,4)}	3.74 ± 0.0086	2.75 ± 0.0078	2.81 ± 0.0077	2.72 ± 0.0077	3.40 ± 0.0080	2.35 ± 0.0071	2.52 ± 0.0069	2.22 ± 0.0068
3 {3,0.75,(4,2),(8,4)}	6.04 ± 0.0100	5.64 ± 0.0108	6.03 ± 0.0098	5.77 ± 0.0106	5.79 ± 0.0099	5.43 ± 0.0106	5.76 ± 0.0097	5.57 ± 0.0105
4 {4,0.75,(4,2),(8,4)}	4.20 ± 0.0086	3.38 ± 0.0084	3.49 ± 0.0081	3.39 ± 0.0083	3.72 ± 0.0080	2.82 ± 0.0075	3.04 ± 0.0072	2.78 ± 0.0074
5 {3,1,(4,2),(8,4)}	6.44 ± 0.0101	6.02 ± 0.0111	6.41 ± 0.0098	6.17 ± 0.0109	6.20 ± 0.0099	5.87 ± 0.0110	6.17 ± 0.0097	5.99 ± 0.0109
6 {4,1,(4,2),(8,4)}	4.33 ± 0.0086	3.46 ± 0.0083	3.59 ± 0.0079	3.48 ± 0.0081	3.91 ± 0.0080	2.96 ± 0.0074	3.18 ± 0.0070	2.95 ± 0.0072
7 {3,0.5,(8,4),(8,4)}	8.34 ± 0.0114	7.82 ± 0.0121	8.18 ± 0.0124	7.89 ± 0.0134	7.92 ± 0.0114	7.45 ± 0.0121	7.83 ± 0.0113	7.52 ± 0.0120
8 {4,0.5,(8,4),(8,4)}	4.63 ± 0.0098	3.62 ± 0.0093	3.85 ± 0.0093	3.58 ± 0.0091	4.05 ± 0.0090	3.00 ± 0.0084	3.30 ± 0.0083	2.94 ± 0.0082
9 {3,0.75,(8,4),(8,4)}	8.73 ± 0.0113	8.14 ± 0.0123	8.57 ± 0.0112	8.28 ± 0.0122	8.30 ± 0.0113	7.80 ± 0.0123	8.20 ± 0.0112	7.89 ± 0.0122
10 {4,0.75,(8,4),(8,4)}	4.36 ± 0.0093	3.53 ± 0.0090	3.63 ± 0.0087	3.44 ± 0.0088	3.92 ± 0.0086	2.91 ± 0.0080	3.17 ± 0.0078	2.87 ± 0.0079
11 {3,1,(8,4),(8,4)}	7.36 ± 0.0112	6.84 ± 0.0123	7.28 ± 0.0109	7.09 ± 0.0121	7.07 ± 0.0111	6.61 ± 0.0122	7.07 ± 0.0108	6.80 ± 0.0120
12 {4,1,(8,4),(8,4)}	5.55 ± 0.0099	4.54 ± 0.0099	4.79 ± 0.0095	4.55 ± 0.0097	4.86 ± 0.0091	3.81 ± 0.0089	4.17 ± 0.0085	3.78 ± 0.0087
13 {3,0.5,(12,6),(8,4)}	9.10 ± 0.0130	8.47 ± 0.0136	8.88 ± 0.0129	8.54 ± 0.0136	8.61 ± 0.0130	8.13 ± 0.0136	8.44 ± 0.0128	8.25 ± 0.0136
14 {4,0.5,(12,6),(8,4)}	4.22 ± 0.0102	3.18 ± 0.0094	3.37 ± 0.0094	3.14 ± 0.0092	3.73 ± 0.0094	2.67 ± 0.0085	2.95 ± 0.0085	2.61 ± 0.0082
15 {3,0.75,(12,6),(8,4)}	8.12 ± 0.0127	7.54 ± 0.0136	8.02 ± 0.0126	7.69 ± 0.0134	7.73 ± 0.0126	7.30 ± 0.0135	7.68 ± 0.0124	7.52 ± 0.0133
16 {4,0.75,(12,6),(8,4)}	4.26 ± 0.0100	3.31 ± 0.0093	3.46 ± 0.0091	3.30 ± 0.0091	3.81 ± 0.0091	2.85 ± 0.0084	3.05 ± 0.0082	2.78 ± 0.0081
17 {3,1,(12,6),(8,4)}	8.64 ± 0.0128	8.12 ± 0.0139	8.56 ± 0.0125	8.22 ± 0.0137	8.22 ± 0.0127	7.80 ± 0.0138	8.21 ± 0.0123	7.94 ± 0.0136
18 {4,1,(12,6),(8,4)}	4.27 ± 0.0098	3.37 ± 0.0091	3.49 ± 0.0089	3.38 ± 0.0089	3.85 ± 0.0090	2.94 ± 0.0083	3.18 ± 0.0080	2.94 ± 0.0080
19 {3,0.5,(20,10),(8,4)}	10.61 ± 0.0172	9.90 ± 0.0177	10.48 ± 0.0171	9.94 ± 0.0177	10.15 ± 0.0171	9.51 ± 0.0177	9.91 ± 0.0171	9.61 ± 0.0176
20 {4,0.5,(20,10),(8,4)}	5.26 ± 0.0134	3.99 ± 0.0124	4.22 ± 0.0126	3.85 ± 0.0119	4.54 ± 0.0123	3.37 ± 0.0115	3.64 ± 0.0114	3.18 ± 0.0109
21 {3,0.75,(20,10),(8,4)}	10.88 ± 0.0172	10.12 ± 0.0180	10.66 ± 0.0171	10.11 ± 0.0179	10.37 ± 0.0171	9.75 ± 0.0180	10.19 ± 0.0170	9.82 ± 0.0179
22 {4,0.75,(20,10),(8,4)}	5.50 ± 0.0138	4.13 ± 0.0125	4.50 ± 0.0128	4.06 ± 0.0122	4.77 ± 0.0126	3.56 ± 0.0117	3.92 ± 0.0116	3.49 ± 0.0113
23 {3,1,(20,10),(8,4)}	10.20 ± 0.0170	9.29 ± 0.0179	9.73 ± 0.0169	9.28 ± 0.0179	9.69 ± 0.0170	8.99 ± 0.0178	9.34 ± 0.0167	9.03 ± 0.0178
24 {4,1,(20,10),(8,4)}	6.25 ± 0.0140	5.01 ± 0.0134	5.34 ± 0.0134	4.92 ± 0.0130	5.47 ± 0.0130	4.29 ± 0.0125	4.63 ± 0.0122	4.20 ± 0.0122
25 {3,0.5,(4,2),(8,6)}	9.63 ± 0.0117	8.69 ± 0.0123	9.11 ± 0.0117	8.59 ± 0.0122	8.91 ± 0.0115	8.12 ± 0.0119	8.45 ± 0.0113	7.99 ± 0.0118
26 {4,0.5,(4,2),(8,6)}	5.06 ± 0.0102	4.06 ± 0.0098	4.25 ± 0.0096	4.04 ± 0.0098	4.26 ± 0.0091	3.09 ± 0.0083	3.43 ± 0.0082	2.99 ± 0.0081
27 {3,0.75,(4,2),(8,6)}	9.19 ± 0.0118	8.20 ± 0.0124	8.77 ± 0.0116	8.25 ± 0.0123	8.52 ± 0.0115	7.84 ± 0.0121	8.10 ± 0.0112	7.75 ± 0.0120
28 {4,0.75,(4,2),(8,6)}	4.39 ± 0.0094	3.43 ± 0.0090	3.47 ± 0.0085	3.36 ± 0.0088	3.88 ± 0.0085	2.75 ± 0.0076	2.95 ± 0.0073	2.65 ± 0.0073
29 {3,1,(4,2),(8,6)}	10.37 ± 0.0117	9.36 ± 0.0126	9.88 ± 0.0115	9.34 ± 0.0126	9.63 ± 0.0115	8.82 ± 0.0123	9.10 ± 0.0111	8.75 ± 0.0122
30 {4,1,(4,2),(8,6)}	5.13 ± 0.0098	4.20 ± 0.0097	4.32 ± 0.0091	4.20 ± 0.0096	4.43 ± 0.0087	3.33 ± 0.0081	3.66 ± 0.0078	3.29 ± 0.0079
31 {3,0.5,(8,4),(8,6)}	9.78 ± 0.0127	8.97 ± 0.0132	9.53 ± 0.0129	9.03 ± 0.0131	9.12 ± 0.0124	8.50 ± 0.0129	8.88 ± 0.0123	8.48 ± 0.0129
32 {4,0.5,(8,4),(8,6)}	4.92 ± 0.0106	3.75 ± 0.0099	3.89 ± 0.0098	3.74 ± 0.0099	4.20 ± 0.0094	2.95 ± 0.0085	3.21 ± 0.0084	2.81 ± 0.0082
33 {3,0.75,(8,4),(8,6)}	8.33 ± 0.0124	7.59 ± 0.0131	8.12 ± 0.0121	7.75 ± 0.0129	7.91 ± 0.0121	7.31 ± 0.0128	7.68 ± 0.0117	7.34 ± 0.0126
34 {4,0.75,(8,4),(8,6)}	4.79 ± 0.0102	3.77 ± 0.0098	3.79 ± 0.0092	3.74 ± 0.0095	4.20 ± 0.0091	2.99 ± 0.0082	3.32 ± 0.0081	2.93 ± 0.0079
35 {3,1,(8,4),(8,6)}	9.26 ± 0.0125	8.53 ± 0.0135	9.10 ± 0.0120	8.62 ± 0.0132	8.66 ± 0.0122	8.07 ± 0.0132	8.61 ± 0.0117	8.22 ± 0.0128
36 {4,1,(8,4),(8,6)}	5.46 ± 0.0105	4.46 ± 0.0103	4.61 ± 0.0099	4.44 ± 0.0102	4.71 ± 0.0093	3.57 ± 0.0088	3.88 ± 0.0085	3.53 ± 0.0085
37 {3,0.5,(12,6),(8,6)}	9.36 ± 0.0142	8.61 ± 0.0146	9.22 ± 0.0142	8.71 ± 0.0147	8.86 ± 0.0139	8.21 ± 0.0143	8.58 ± 0.0137	8.21 ± 0.0144
38 {4,0.5,(12,6),(8,6)}	4.66 ± 0.0110	3.40 ± 0.0101	3.48 ± 0.0099	3.27 ± 0.0097	4.10 ± 0.0099	2.71 ± 0.0086	2.96 ± 0.0086	2.62 ± 0.0083
39 {3,0.75,(12,6),(8,6)}	10.89 ± 0.0142	10.05 ± 0.0149	10.61 ± 0.0139	10.09 ± 0.0148	10.23 ± 0.0138	9.51 ± 0.0146	10.01 ± 0.0136	9.48 ± 0.0145
40 {4,0.75,(12,6),(8,6)}	5.03 ± 0.0110	3.82 ± 0.0103	3.96 ± 0.0100	3.75 ± 0.0100	4.39 ± 0.0099	3.12 ± 0.0089	3.40 ± 0.0087	3.04 ± 0.0086
41 {3,1,(12,6),(8,6)}	9.85 ± 0.0139	9.06 ± 0.0149	9.71 ± 0.0136	9.22 ± 0.0147	9.23 ± 0.0135	8.62 ± 0.0146	9.11 ± 0.0131	8.79 ± 0.0143
42 {4,1,(12,6),(8,6)}	4.64 ± 0.0105	3.66 ± 0.0099	3.73 ± 0.0095	3.59 ± 0.0096	4.12 ± 0.0094	3.05 ± 0.0086	3.28 ± 0.0084	2.98 ± 0.0082
43 {3,0.5,(20,10),(8,6)}	12.43 ± 0.0189	11.33 ± 0.0195	11.76 ± 0.0188	11.18 ± 0.0194	11.79 ± 0.0188	10.79 ± 0.0193	11.11 ± 0.0186	10.56 ± 0.0192
44 {4,0.5,(20,10),(8,6)}	5.36 ± 0.0137	3.81 ± 0.0123	4.03 ± 0.0125	3.71 ± 0.0119	4.60 ± 0.0124	3.12 ± 0.0110	3.48 ± 0.0112	2.97 ± 0.0105
45 {3,0.75,(20,10),(8,6)}	10.45 ± 0.0176	9.48 ± 0.0181	10.12 ± 0.0174	9.62 ± 0.0180	9.79 ± 0.0172	9.10 ± 0.0178	9.63 ± 0.0171	9.15 ± 0.0177
46 {4,0.75,(20,10),(8,6)}	5.27 ± 0.0133	3.96 ± 0.0122	4.11 ± 0.0122	3.84 ± 0.0118	4.55 ± 0.0120	3.30 ± 0.0110	3.57 ± 0.0109	3.14 ± 0.0105
47 {3,1,(20,10),(8,6)}	12.00 ± 0.0182	11.05 ± 0.0193	11.78 ± 0.0180	11.20 ± 0.0191	11.29 ± 0.0179	10.49 ± 0.0189	11.15 ± 0.0177	10.65 ± 0.0188
48 {4,1,(20,10),(8,6)}	6.19 ± 0.0142	4.79 ± 0.0133	5.13 ± 0.0132	4.80 ± 0.0129	5.46 ± 0.0130	4.02 ± 0.0120	4.41 ± 0.0118	3.90 ± 0.0115
49 {3,0.5,(4,2),(8,8)}	8.84 ± 0.0136	7.72 ± 0.0134	8.09 ± 0.0131	7.55 ± 0.0133	8.18 ± 0.0129	7.23 ± 0.0128	7.55 ± 0.0124	7.06 ± 0.0127
50 {4,0.5,(4,2),(8,8)}	3.97 ± 0.0100	3.07 ± 0.0095	2.89 ± 0.0086	2.97 ± 0.0092	3.43 ± 0.0089	2.25 ± 0.0073	2.45 ± 0.0074	2.15 ± 0.0070
51 {3,0.75,(4,2),(8,8)}	10.52 ± 0.0137	9.26 ± 0.0140	9.74 ± 0.0139	9.08 ± 0.0139	9.58 ± 0.0130	8.52 ± 0.0133	8.99 ± 0.0127	8.47 ± 0.0133
52 {4,0.75,(4,2),(8,8)}	5.71 ± 0.0113	4.51 ± 0.0110	4.58 ± 0.0104	4.50 ± 0.0109	4.76 ± 0.0098	3.36 ± 0.0087	3.76 ± 0.0087	3.23 ± 0.0084
53 {3,1,(4,2),(8,8)}	10.31 ± 0.0137	9.17 ± 0.0142	9.77 ± 0.0132	9.05 ± 0.0140	9.53 ± 0.0130	8.53 ± 0.0135	9.01 ± 0.0125	8.48 ± 0.0134
54 {4,1,(4,2),(8,8)}	4.77 ± 0.0103	3.79 ± 0.0099	3.72 ± 0.0089	3.82 ± 0.0098	4.23 ± 0.0091	2.97 ± 0.0078	3.19 ± 0.0076	2.91 ± 0.0075
55 {3,0.5,(8,4),(8,8)}	9.62 ± 0.0144	8.70 ± 0.0145	9.18 ± 0.0140	8.59 ± 0.0143	8.95 ± 0.0137	8.19 ± 0.0138	8.50 ± 0.0133	8.10 ± 0.0136
56 {4,0.5,(8,4),(8,8)}	5.62 ± 0.0120	4.26 ± 0.0112	4.27 ± 0.0108	4.20 ± 0.0111	4.71 ± 0.0104	3.15 ± 0.0090	3.51 ± 0.0091	3.01 ± 0.0086
57 {3,0.75,(8,4),(8,8)}	11.12 ± 0.0145	10.22 ± 0.0151	10.86 ± 0.0142	10.15 ± 0.0148	10.30 ± 0.0138	9.42 ± 0.0144	9.94 ± 0.0135	9.35 ± 0.0141
58 {4,0.75,(8,4),(8,8)}	5.94 ± 0.0118	4.60 ± 0.0114	4.71 ± 0.0109	4.49 ± 0.0111	5.07 ± 0.0103	3.50 ± 0.0091	3.91 ± 0.0091	3.35 ± 0.0088
59 {3,1,(8,4),(8,8)}	9.28 ± 0.0140	8.42 ± 0.0147	9.15 ± 0.0135	8.79 ± 0.0146	8.62 ± 0.0133	7.93 ± 0.0141	8.48 ± 0.0128	8.17 ± 0.0139
60 {4,1,(8,4),(8,8)}	5.50 ± 0.0114	4.38 ± 0.0110	4.47 ± 0.0102	4.44 ± 0.0108	4.69 ± 0.0098	3.45 ± 0.0089	3.79 ± 0.0086	3.43 ± 0.0086
61 {3,0.5,(12,6),(8,8)}	11.84 ± 0.0161	10.89 ± 0.0164	11.31 ± 0.0159	10.61 ± 0.0162	11.00 ± 0.0154	10.03 ± 0.0158	10.33 ± 0.0152	9.88 ± 0.0157

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Table A.2: – continued from previous page

Instance $\{\hat{T}, \gamma, (\alpha_1, \beta_1), (\alpha_i, \beta_i)\}$	Average cost per time unit and 95% confidence interval of heuristic n							
	1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
62 {4,0.5,(12,6),(8,8)}	4.51 ± 0.0115	3.23 ± 0.0103	3.24 ± 0.0099	3.20 ± 0.0101	3.95 ± 0.0102	2.56 ± 0.0085	2.77 ± 0.0085	2.41 ± 0.0081
63 {3,0.75,(12,6),(8,8)}	11.88 ± 0.0158	10.82 ± 0.0163	11.62 ± 0.0156	11.01 ± 0.0163	11.04 ± 0.0151	10.20 ± 0.0157	10.77 ± 0.0149	10.28 ± 0.0156
64 {4,0.75,(12,6),(8,8)}	5.62 ± 0.0124	4.40 ± 0.0119	4.47 ± 0.0113	4.36 ± 0.0116	4.84 ± 0.0109	3.35 ± 0.0096	3.77 ± 0.0096	3.30 ± 0.0093
65 {3,1,(12,6),(8,8)}	10.87 ± 0.0156	9.86 ± 0.0164	10.83 ± 0.0153	10.20 ± 0.0164	10.21 ± 0.0150	9.25 ± 0.0158	10.05 ± 0.0145	9.52 ± 0.0156
66 {4,1,(12,6),(8,8)}	5.37 ± 0.0119	4.25 ± 0.0114	4.27 ± 0.0106	4.24 ± 0.0111	4.68 ± 0.0104	3.39 ± 0.0093	3.66 ± 0.0091	3.29 ± 0.0089
67 {3,0.5,(20,10),(8,8)}	10.99 ± 0.0193	10.01 ± 0.0195	10.73 ± 0.0191	10.18 ± 0.0195	10.31 ± 0.0188	9.51 ± 0.0190	10.05 ± 0.0187	9.57 ± 0.0190
68 {4,0.5,(20,10),(8,8)}	5.13 ± 0.0141	3.84 ± 0.0128	3.94 ± 0.0128	3.69 ± 0.0124	4.35 ± 0.0125	2.97 ± 0.0109	3.27 ± 0.0112	2.80 ± 0.0104
69 {3,0.75,(20,10),(8,8)}	13.08 ± 0.0192	11.87 ± 0.0196	12.77 ± 0.0190	12.06 ± 0.0197	12.18 ± 0.0185	11.17 ± 0.0190	11.97 ± 0.0183	11.32 ± 0.0190
70 {4,0.75,(20,10),(8,8)}	5.87 ± 0.0141	4.49 ± 0.0133	4.57 ± 0.0129	4.33 ± 0.0127	5.03 ± 0.0126	3.49 ± 0.0112	3.84 ± 0.0112	3.33 ± 0.0106
71 {3,1,(20,10),(8,8)}	14.93 ± 0.0196	13.76 ± 0.0206	14.66 ± 0.0194	13.87 ± 0.0205	13.96 ± 0.0190	12.89 ± 0.0200	13.66 ± 0.0188	12.90 ± 0.0199
72 {4,1,(20,10),(8,8)}	5.61 ± 0.0135	4.25 ± 0.0126	4.29 ± 0.0121	4.09 ± 0.0121	4.97 ± 0.0121	3.44 ± 0.0107	3.69 ± 0.0106	3.32 ± 0.0103

Table A.3: Average cost per time unit and 95% confidence interval for each instance of large symmetric test bed: heuristic 1-4

Instance $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$	Average cost per time unit and 95% confidence interval of heuristic n			
	1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R
1 {100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ 1/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	45.94 ± 0.188	29.08 ± 0.201	40.62 ± 0.223	27.96 ± 0.207
2 {180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ 1/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	138.20 ± 0.484	59.57 ± 0.262	126.02 ± 0.844	57.46 ± 0.345
3 {100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ 1/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	75.69 ± 0.333	50.12 ± 0.205	72.74 ± 0.407	41.03 ± 0.172
4 {180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ 1/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	208.91 ± 1.086	238.58 ± 1.479	212.52 ± 1.148	244.66 ± 1.590
5 {100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ 1/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	28.96 ± 0.145	12.46 ± 0.067	24.61 ± 0.118	12.03 ± 0.058
6 {180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ 1/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	124.99 ± 0.525	32.76 ± 0.144	108.62 ± 0.532	35.37 ± 0.230
7 {100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ 1/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	57.04 ± 0.285	25.09 ± 0.166	51.88 ± 0.259	20.56 ± 0.078
8 {180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ 1/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	194.37 ± 1.108	238.18 ± 1.453	200.44 ± 1.363	236.35 ± 1.300
9 {100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ 2/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	24.93 ± 0.130	23.63 ± 0.087	27.56 ± 0.146	24.10 ± 0.094
10 {180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ 2/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	54.68 ± 0.405	49.27 ± 0.251	55.67 ± 0.217	50.77 ± 0.228
11 {100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ 2/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	24.63 ± 0.106	21.96 ± 0.121	25.93 ± 0.124	22.45 ± 0.144
12 {180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ 2/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	58.49 ± 0.263	37.69 ± 0.253	48.73 ± 0.239	36.74 ± 0.151
13 {100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ 2/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	21.63 ± 0.082	13.87 ± 0.060	15.02 ± 0.068	10.50 ± 0.077
14 {180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ 2/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	37.02 ± 0.248	24.36 ± 0.168	29.17 ± 0.120	22.14 ± 0.080
15 {100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ 2/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	19.89 ± 0.070	12.57 ± 0.065	15.42 ± 0.082	11.60 ± 0.074
16 {180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ 2/10 · N ^d , U[0.001; 0.01], 1, 50, 0.05 · α _i }	46.46 ± 0.204	22.41 ± 0.078	30.79 ± 0.139	19.54 ± 0.068
17 {100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ 1/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	165.91 ± 0.863	153.87 ± 0.954	167.73 ± 0.906	155.71 ± 0.607
18 {180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ 1/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	330.70 ± 1.753	308.16 ± 2.311	330.73 ± 2.249	308.01 ± 2.156
19 {100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ 1/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	184.69 ± 1.090	184.63 ± 0.923	182.71 ± 0.987	184.43 ± 1.125
20 {180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ 1/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	343.39 ± 1.889	340.27 ± 1.837	344.74 ± 1.655	340.58 ± 2.384
21 {100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ 1/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	167.37 ± 0.619	153.74 ± 0.630	165.95 ± 1.079	163.75 ± 1.146
22 {180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ 1/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	324.08 ± 2.236	299.98 ± 2.100	322.57 ± 1.161	300.76 ± 1.594
23 {100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ 1/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	175.67 ± 0.949	178.01 ± 0.890	177.75 ± 1.333	176.97 ± 1.256
24 {180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ 1/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	336.66 ± 2.491	332.99 ± 1.965	338.71 ± 2.168	333.30 ± 2.466
25 {100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ 2/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	90.86 ± 0.618	69.22 ± 0.249	104.80 ± 0.639	70.32 ± 0.464
26 {180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ 2/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	267.05 ± 1.736	140.82 ± 0.732	199.28 ± 0.737	140.37 ± 0.898
27 {100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ 2/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	156.34 ± 1.048	69.62 ± 0.299	121.76 ± 0.828	68.60 ± 0.398
28 {180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ 2/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	335.01 ± 1.642	139.42 ± 0.530	336.39 ± 1.716	132.25 ± 0.939
29 {100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ 2/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	35.31 ± 0.247	19.16 ± 0.077	52.18 ± 0.245	21.55 ± 0.144
30 {180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ 2/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	255.47 ± 1.405	53.87 ± 0.323	309.13 ± 1.855	82.57 ± 0.570
31 {100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ 2/10 · N ^d , U[0.01; 0.05], 1, 50, 0.05 · α _i }	148.47 ± 0.713	39.21 ± 0.200	155.19 ± 0.869	65.41 ± 0.399

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Table A.3: – continued from previous page

Instance $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$		Average cost per time unit and 95% confidence interval of heuristic n			
		1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R
32	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i\}$	326.43 ± 1.502	84.66 ± 0.423	332.72 ± 1.730	226.30 ± 0.996
33	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	59.17 ± 0.408	39.08 ± 0.164	53.95 ± 0.329	38.39 ± 0.184
34	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	174.82 ± 1.049	82.44 ± 0.437	139.73 ± 0.671	77.36 ± 0.387
35	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	102.62 ± 0.616	56.52 ± 0.300	94.72 ± 0.436	53.99 ± 0.329
36	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	260.93 ± 1.748	289.07 ± 1.503	255.72 ± 1.764	290.80 ± 1.541
37	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	71.36 ± 0.528	33.07 ± 0.165	63.88 ± 0.377	35.82 ± 0.251
38	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	162.99 ± 0.717	54.72 ± 0.356	142.89 ± 0.972	61.91 ± 0.322
39	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	94.57 ± 0.643	44.44 ± 0.213	115.42 ± 0.600	159.14 ± 1.194
40	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	275.50 ± 1.157	306.24 ± 1.929	271.49 ± 1.140	312.35 ± 1.718
41	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	30.67 ± 0.113	29.36 ± 0.103	33.12 ± 0.235	31.00 ± 0.130
42	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	63.05 ± 0.366	58.32 ± 0.239	67.11 ± 0.282	58.59 ± 0.434
43	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	33.27 ± 0.230	28.22 ± 0.172	32.16 ± 0.148	27.09 ± 0.176
44	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	100.25 ± 0.521	66.58 ± 0.493	84.80 ± 0.568	61.84 ± 0.315
45	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	42.56 ± 0.285	41.56 ± 0.254	21.63 ± 0.102	17.46 ± 0.075
46	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	54.80 ± 0.236	41.12 ± 0.206	45.43 ± 0.277	32.67 ± 0.229
47	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	25.62 ± 0.164	23.38 ± 0.171	28.37 ± 0.204	21.58 ± 0.112
48	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i\}$	88.57 ± 0.478	58.47 ± 0.286	66.67 ± 0.320	47.97 ± 0.259
49	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	196.80 ± 0.787	180.70 ± 1.211	200.20 ± 0.881	173.86 ± 0.852
50	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	385.15 ± 1.464	368.23 ± 2.393	385.84 ± 2.739	366.57 ± 1.320
51	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	209.27 ± 1.172	211.03 ± 1.351	212.10 ± 1.421	211.63 ± 1.016
52	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	394.96 ± 1.422	394.51 ± 2.959	396.92 ± 2.898	395.27 ± 2.411
53	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	189.28 ± 1.382	159.64 ± 0.846	189.64 ± 1.365	159.69 ± 0.623
54	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	376.77 ± 2.336	349.94 ± 2.065	378.61 ± 1.779	350.89 ± 2.316
55	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	203.00 ± 0.954	204.25 ± 1.287	201.73 ± 1.473	203.62 ± 0.794
56	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	389.90 ± 2.729	384.44 ± 1.730	388.67 ± 2.682	383.50 ± 1.496
57	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	109.04 ± 0.545	85.70 ± 0.583	106.98 ± 0.749	83.38 ± 0.375
58	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	322.77 ± 2.292	177.30 ± 0.887	262.51 ± 1.208	176.05 ± 1.268
59	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	220.66 ± 0.794	100.35 ± 0.692	184.59 ± 0.720	100.20 ± 0.731
60	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	437.18 ± 2.448	212.53 ± 0.978	442.69 ± 1.638	200.68 ± 0.863
61	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	87.69 ± 0.588	50.30 ± 0.201	84.40 ± 0.346	53.31 ± 0.304
62	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	364.13 ± 1.675	105.11 ± 0.683	396.33 ± 1.665	113.97 ± 0.467
63	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	206.40 ± 0.743	77.90 ± 0.436	198.05 ± 0.852	116.81 ± 0.841
64	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i\}$	428.03 ± 1.669	157.94 ± 0.805	422.16 ± 2.111	359.17 ± 1.724
65	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	99.36 ± 0.656	59.45 ± 0.398	89.42 ± 0.635	59.52 ± 0.208
66	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	308.24 ± 2.127	126.82 ± 0.558	270.29 ± 1.757	118.73 ± 0.606
67	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	156.08 ± 0.921	76.91 ± 0.300	146.43 ± 1.010	71.59 ± 0.458
68	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	485.84 ± 3.547	594.73 ± 3.271	494.12 ± 3.360	594.78 ± 3.450
69	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	83.47 ± 0.442	30.52 ± 0.201	98.07 ± 0.598	35.40 ± 0.248
70	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	300.41 ± 2.223	63.59 ± 0.324	361.64 ± 2.314	103.75 ± 0.477
71	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	147.88 ± 0.739	75.35 ± 0.520	169.16 ± 0.913	283.89 ± 1.561
72	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	445.53 ± 2.673	466.66 ± 2.240	441.81 ± 2.960	550.02 ± 2.200
73	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	67.64 ± 0.352	63.43 ± 0.463	70.36 ± 0.338	64.54 ± 0.297
74	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	115.76 ± 0.544	101.46 ± 0.436	117.89 ± 0.613	102.18 ± 0.562
75	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	78.74 ± 0.457	64.47 ± 0.309	75.58 ± 0.348	64.11 ± 0.468
76	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	128.44 ± 0.938	84.42 ± 0.591	118.30 ± 0.438	86.38 ± 0.579
77	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	20.52 ± 0.101	16.52 ± 0.114	30.65 ± 0.132	15.09 ± 0.100

Continued on next page

Table A.3: – continued from previous page

		Average cost per time unit and 95% confidence interval of heuristic n			
Instance		1	2	3	4
$\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$		SDSR	SDSR-R	SDDR	SDDR-R
78	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	44.35 ± 0.182	26.38 ± 0.161	49.05 ± 0.368	25.06 ± 0.148
79	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	14.14 ± 0.103	11.97 ± 0.059	23.23 ± 0.132	12.56 ± 0.058
80	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.05 \cdot \alpha_i\}$	96.06 ± 0.557	34.37 ± 0.134	75.45 ± 0.332	38.63 ± 0.209
81	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	401.64 ± 2.530	351.57 ± 2.039	405.70 ± 2.759	344.46 ± 2.480
82	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	792.90 ± 5.788	763.22 ± 5.266	795.03 ± 4.929	750.66 ± 3.979
83	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	435.21 ± 1.915	437.78 ± 1.839	441.12 ± 3.264	434.71 ± 2.695
84	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	835.97 ± 6.019	813.55 ± 4.312	835.38 ± 4.010	817.02 ± 3.105
85	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	385.68 ± 2.353	340.96 ± 2.523	406.88 ± 2.319	372.92 ± 1.529
86	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	794.14 ± 4.209	739.58 ± 2.810	794.39 ± 3.734	736.79 ± 2.947
87	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	421.01 ± 2.484	422.69 ± 2.325	420.01 ± 3.150	420.37 ± 1.766
88	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	817.43 ± 5.967	796.05 ± 5.652	811.14 ± 3.893	797.48 ± 4.386
89	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	226.43 ± 0.928	154.74 ± 0.805	257.57 ± 1.030	155.68 ± 0.545
90	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	631.75 ± 4.296	329.25 ± 2.107	686.59 ± 4.600	326.53 ± 2.057
91	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	367.42 ± 2.315	162.59 ± 0.829	358.91 ± 2.010	154.01 ± 0.755
92	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	790.78 ± 4.270	308.00 ± 2.187	790.58 ± 4.506	319.11 ± 1.500
93	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	153.01 ± 0.612	65.24 ± 0.424	203.14 ± 1.361	79.84 ± 0.471
94	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	496.46 ± 2.631	111.08 ± 0.655	667.17 ± 3.269	141.69 ± 0.808
95	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	334.62 ± 2.008	76.46 ± 0.336	369.36 ± 1.440	101.80 ± 0.407
96	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.05 \cdot \alpha_i\}$	770.51 ± 4.469	191.29 ± 1.396	783.37 ± 5.014	212.96 ± 1.278
97	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	125.24 ± 0.676	69.84 ± 0.314	107.21 ± 0.740	70.58 ± 0.374
98	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	355.80 ± 2.277	153.36 ± 1.150	320.07 ± 1.504	151.35 ± 0.938
99	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	182.44 ± 0.912	96.05 ± 0.624	170.68 ± 1.075	93.90 ± 0.366
100	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	551.52 ± 3.144	641.38 ± 3.271	540.23 ± 3.241	645.15 ± 2.387
101	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	126.27 ± 0.859	52.32 ± 0.303	117.96 ± 0.672	55.94 ± 0.213
102	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	293.60 ± 1.174	86.68 ± 0.338	264.46 ± 1.587	86.53 ± 0.623
103	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	159.21 ± 0.892	58.83 ± 0.329	167.18 ± 0.752	301.39 ± 1.386
104	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	550.75 ± 3.084	628.48 ± 3.268	555.57 ± 3.722	629.61 ± 4.281
105	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	71.16 ± 0.306	64.26 ± 0.360	76.30 ± 0.366	65.88 ± 0.349
106	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	142.72 ± 0.571	128.11 ± 0.512	146.81 ± 0.646	129.36 ± 0.699
107	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	85.00 ± 0.484	65.54 ± 0.380	79.71 ± 0.399	63.95 ± 0.339
108	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	156.17 ± 1.062	109.84 ± 0.604	159.30 ± 0.701	110.00 ± 0.649
109	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	37.55 ± 0.244	30.82 ± 0.114	74.35 ± 0.283	24.11 ± 0.123
110	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	66.89 ± 0.334	50.62 ± 0.339	75.80 ± 0.341	42.86 ± 0.201
111	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	50.21 ± 0.306	31.52 ± 0.195	70.12 ± 0.280	31.50 ± 0.176
112	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.05 \cdot \alpha_i\}$	294.19 ± 1.147	109.98 ± 0.671	210.92 ± 1.582	103.78 ± 0.446
113	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.05 \cdot \alpha_i\}$	439.99 ± 3.168	402.80 ± 2.095	437.44 ± 2.625	387.83 ± 2.443
114	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.05 \cdot \alpha_i\}$	857.52 ± 4.802	807.99 ± 5.737	856.52 ± 3.597	812.99 ± 3.089
115	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.05 \cdot \alpha_i\}$	464.53 ± 2.741	474.48 ± 2.515	464.68 ± 2.927	474.58 ± 3.464
116	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.05 \cdot \alpha_i\}$	890.81 ± 6.414	887.62 ± 6.036	895.21 ± 4.476	890.30 ± 6.143
117	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.05 \cdot \alpha_i\}$	408.22 ± 2.082	288.60 ± 1.039	432.17 ± 2.420	414.26 ± 2.361
118	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.05 \cdot \alpha_i\}$	834.56 ± 4.006	775.50 ± 3.102	839.03 ± 4.027	781.30 ± 4.766
119	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.05 \cdot \alpha_i\}$	444.41 ± 3.244	449.98 ± 2.430	441.49 ± 1.854	452.56 ± 2.896
120	$\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.05 \cdot \alpha_i\}$	873.94 ± 4.020	866.58 ± 3.380	875.25 ± 6.389	867.14 ± 4.509
121	$\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.05 \cdot \alpha_i\}$	221.03 ± 1.105	170.73 ± 1.093	341.29 ± 1.365	172.85 ± 1.020
122	$\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.05 \cdot \alpha_i\}$	628.62 ± 3.646	354.27 ± 1.382	602.71 ± 2.531	353.86 ± 1.486
123	$\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.05 \cdot \alpha_i\}$	438.65 ± 2.281	197.56 ± 1.126	433.62 ± 2.949	200.14 ± 0.801

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Table A.3: – continued from previous page

Instance $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$	Average cost per time unit and 95% confidence interval of heuristic n			
	1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R
124 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, $0.05 \cdot \alpha_i$ }	888.47 ± 3.465	374.17 ± 2.731	882.25 ± 5.205	378.01 ± 1.625
125 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, $0.05 \cdot \alpha_i$ }	122.24 ± 0.501	70.23 ± 0.471	298.63 ± 1.851	75.20 ± 0.481
126 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, $0.05 \cdot \alpha_i$ }	597.48 ± 3.047	150.03 ± 1.065	759.68 ± 5.622	191.37 ± 0.670
127 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, $0.05 \cdot \alpha_i$ }	377.58 ± 2.832	113.38 ± 0.703	385.71 ± 2.083	118.69 ± 0.653
128 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, $0.05 \cdot \alpha_i$ }	854.57 ± 4.358	248.48 ± 1.590	861.13 ± 6.458	320.78 ± 1.251
129 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	52.81 ± 0.380	31.98 ± 0.154	48.54 ± 0.209	31.35 ± 0.125
130 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	238.52 ± 1.527	63.96 ± 0.307	139.15 ± 0.668	62.72 ± 0.270
131 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	145.55 ± 0.771	48.20 ± 0.217	125.53 ± 0.916	43.57 ± 0.309
132 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	724.28 ± 3.621	980.39 ± 5.294	730.73 ± 4.311	981.15 ± 4.023
133 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	66.80 ± 0.254	19.29 ± 0.091	68.39 ± 0.376	29.49 ± 0.124
134 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	182.52 ± 1.059	34.53 ± 0.242	208.10 ± 1.041	47.82 ± 0.201
135 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	136.01 ± 1.020	250.22 ± 1.676	205.29 ± 1.109	469.14 ± 3.519
136 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	694.89 ± 3.891	933.38 ± 5.974	694.31 ± 4.652	938.39 ± 5.443
137 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	31.21 ± 0.197	28.63 ± 0.163	30.28 ± 0.145	28.83 ± 0.150
138 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	55.31 ± 0.409	48.28 ± 0.256	53.62 ± 0.349	47.09 ± 0.353
139 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	38.91 ± 0.280	27.19 ± 0.193	36.53 ± 0.252	28.37 ± 0.108
140 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	54.63 ± 0.202	38.33 ± 0.192	51.57 ± 0.232	37.70 ± 0.147
141 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	12.27 ± 0.043	9.48 ± 0.068	10.09 ± 0.066	7.36 ± 0.055
142 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	42.03 ± 0.273	26.62 ± 0.109	29.46 ± 0.209	21.78 ± 0.150
143 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	9.78 ± 0.058	8.75 ± 0.040	10.47 ± 0.071	8.47 ± 0.036
144 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, $0.1 \cdot \alpha_i$ }	44.73 ± 0.300	23.78 ± 0.083	33.40 ± 0.150	24.12 ± 0.106
145 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	385.33 ± 1.541	344.78 ± 1.793	375.43 ± 2.440	337.63 ± 1.756
146 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	1169.63 ± 5.380	1018.14 ± 3.564	1178.95 ± 4.480	1018.10 ± 3.563
147 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	662.50 ± 4.505	698.26 ± 3.980	662.48 ± 4.240	706.11 ± 4.590
148 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	1417.57 ± 7.938	1467.47 ± 9.098	1427.90 ± 10.424	1460.26 ± 5.111
149 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	390.55 ± 1.953	211.85 ± 1.229	388.52 ± 2.875	404.43 ± 1.496
150 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	1117.43 ± 6.258	1011.51 ± 3.540	1130.80 ± 7.689	1002.29 ± 5.312
151 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	611.93 ± 4.345	690.81 ± 3.799	685.92 ± 2.538	777.43 ± 5.753
152 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	1392.08 ± 6.960	1403.55 ± 7.720	1394.12 ± 7.807	1406.39 ± 6.469
153 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	95.29 ± 0.343	71.77 ± 0.517	98.90 ± 0.405	71.90 ± 0.395
154 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	301.19 ± 1.596	149.33 ± 0.762	211.97 ± 1.060	146.05 ± 1.022
155 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	281.98 ± 1.241	81.54 ± 0.318	205.63 ± 1.172	80.07 ± 0.336
156 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	990.33 ± 3.961	178.76 ± 1.287	982.26 ± 4.911	167.26 ± 0.853
157 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	72.28 ± 0.376	24.88 ± 0.097	62.67 ± 0.370	28.89 ± 0.205
158 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	430.40 ± 1.894	62.70 ± 0.238	638.80 ± 3.769	78.66 ± 0.488
159 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	224.00 ± 1.411	45.12 ± 0.284	268.86 ± 1.506	61.71 ± 0.383
160 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, $0.1 \cdot \alpha_i$ }	962.91 ± 3.948	114.36 ± 0.686	1055.30 ± 4.643	836.65 ± 5.020
161 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, $0.1 \cdot \alpha_i$ }	68.63 ± 0.357	37.72 ± 0.140	55.19 ± 0.287	35.47 ± 0.259
162 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, $0.1 \cdot \alpha_i$ }	239.80 ± 1.487	78.83 ± 0.292	139.08 ± 0.862	75.77 ± 0.386
163 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, $0.1 \cdot \alpha_i$ }	141.40 ± 0.877	60.50 ± 0.454	117.55 ± 0.670	55.75 ± 0.290
164 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, $0.1 \cdot \alpha_i$ }	809.92 ± 4.617	1007.99 ± 5.242	786.28 ± 2.831	1020.50 ± 7.552
165 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, $0.1 \cdot \alpha_i$ }	86.21 ± 0.431	32.76 ± 0.131	75.92 ± 0.296	38.54 ± 0.177
166 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, $0.1 \cdot \alpha_i$ }	281.15 ± 2.052	63.65 ± 0.369	253.12 ± 1.797	71.98 ± 0.367
167 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, $0.1 \cdot \alpha_i$ }	142.27 ± 0.683	54.11 ± 0.298	180.02 ± 1.224	362.81 ± 2.612
168 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, $0.1 \cdot \alpha_i$ }	795.39 ± 4.534	1038.92 ± 6.857	768.01 ± 5.607	1057.65 ± 5.182
169 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, $0.1 \cdot \alpha_i$ }	45.99 ± 0.304	41.05 ± 0.205	39.19 ± 0.219	34.81 ± 0.132

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Table A.3: – continued from previous page

Instance $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$	Average cost per time unit and 95% confidence interval of heuristic n			
	1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R
170 {180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 4, 50, 0.1 · α _i }	68.44 ± 0.404	59.46 ± 0.440	68.31 ± 0.307	57.97 ± 0.435
171 {100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 4, 50, 0.1 · α _i }	37.47 ± 0.274	31.87 ± 0.233	38.25 ± 0.245	31.15 ± 0.168
172 {180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 4, 50, 0.1 · α _i }	109.56 ± 0.614	73.31 ± 0.352	87.04 ± 0.505	64.44 ± 0.400
173 {100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 4, 50, 0.1 · α _i }	13.28 ± 0.057	12.12 ± 0.045	16.14 ± 0.092	12.24 ± 0.072
174 {180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 4, 50, 0.1 · α _i }	83.09 ± 0.523	65.14 ± 0.313	53.59 ± 0.198	37.70 ± 0.158
175 {100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 4, 50, 0.1 · α _i }	42.17 ± 0.236	29.92 ± 0.117	29.96 ± 0.105	23.35 ± 0.145
176 {180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 4, 50, 0.1 · α _i }	95.44 ± 0.544	59.85 ± 0.419	76.41 ± 0.481	53.79 ± 0.307
177 {100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	427.94 ± 1.626	383.55 ± 2.685	405.79 ± 2.191	355.62 ± 2.418
178 {180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	1208.26 ± 6.887	1121.59 ± 5.832	1217.26 ± 6.208	1118.78 ± 3.916
179 {100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	679.95 ± 3.264	730.34 ± 3.140	676.39 ± 4.802	737.30 ± 4.276
180 {180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	1470.05 ± 8.673	1477.32 ± 9.603	1476.94 ± 8.419	1475.78 ± 7.379
181 {100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	379.48 ± 2.846	256.97 ± 1.490	500.11 ± 1.750	563.99 ± 2.538
182 {180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	1186.84 ± 7.477	1056.36 ± 7.606	1191.89 ± 8.105	1062.04 ± 4.673
183 {100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	638.84 ± 2.300	686.28 ± 4.255	678.88 ± 3.462	733.93 ± 3.009
184 {180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	1406.14 ± 8.296	1435.17 ± 8.037	1410.38 ± 5.783	1439.87 ± 6.911
185 {100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	107.70 ± 0.528	78.94 ± 0.300	106.67 ± 0.405	78.81 ± 0.449
186 {180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	399.16 ± 1.597	184.93 ± 0.758	279.90 ± 1.567	180.23 ± 1.334
187 {100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	292.57 ± 1.375	93.10 ± 0.633	195.67 ± 1.213	92.66 ± 0.482
188 {180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	1135.32 ± 8.401	233.03 ± 1.678	1196.73 ± 6.582	257.04 ± 0.951
189 {100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	63.69 ± 0.312	41.89 ± 0.214	77.80 ± 0.467	44.51 ± 0.160
190 {180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	551.85 ± 3.421	112.65 ± 0.653	721.22 ± 3.101	125.18 ± 0.926
191 {100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	285.22 ± 1.626	72.16 ± 0.534	331.90 ± 1.361	84.11 ± 0.395
192 {180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.01; 0.05], 4, 50, 0.1 · α _i }	1054.79 ± 4.008	183.19 ± 1.319	1083.06 ± 7.690	188.07 ± 0.733
193 {100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	143.83 ± 0.762	84.76 ± 0.458	126.42 ± 0.796	81.88 ± 0.426
194 {180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	481.39 ± 2.600	140.41 ± 0.969	300.48 ± 1.262	136.89 ± 0.671
195 {100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	293.79 ± 2.057	113.58 ± 0.818	274.13 ± 1.316	104.16 ± 0.760
196 {180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	1702.08 ± 7.489	2379.55 ± 15.943	1728.19 ± 10.369	2268.85 ± 12.932
197 {100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	63.07 ± 0.322	20.08 ± 0.082	76.10 ± 0.350	19.31 ± 0.120
198 {180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	596.78 ± 3.461	71.60 ± 0.501	771.74 ± 5.248	84.90 ± 0.637
199 {100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	263.42 ± 1.870	177.60 ± 1.190	263.76 ± 1.451	106.81 ± 0.694
200 {180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	1726.08 ± 8.458	2275.49 ± 15.246	1745.13 ± 6.108	2220.01 ± 14.208
201 {100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	56.35 ± 0.197	52.30 ± 0.230	60.30 ± 0.217	54.81 ± 0.291
202 {180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	144.11 ± 0.533	121.38 ± 0.510	142.98 ± 0.729	125.70 ± 0.804
203 {100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	52.59 ± 0.205	42.54 ± 0.268	56.12 ± 0.314	44.43 ± 0.182
204 {180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	136.55 ± 0.560	90.02 ± 0.351	133.86 ± 0.924	91.18 ± 0.447
205 {100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	28.09 ± 0.183	20.17 ± 0.141	36.41 ± 0.149	20.64 ± 0.078
206 {180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	47.41 ± 0.284	30.48 ± 0.219	69.92 ± 0.273	32.18 ± 0.190
207 {100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	34.63 ± 0.229	21.16 ± 0.106	53.96 ± 0.405	22.72 ± 0.082
208 {180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ ² / ₁₀ · N ^d], U[0.001; 0.01], 1, 500, 0.1 · α _i }	94.56 ± 0.577	41.70 ± 0.200	82.90 ± 0.307	44.28 ± 0.279
209 {100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 1, 500, 0.1 · α _i }	960.20 ± 6.337	966.64 ± 6.477	965.29 ± 6.757	923.89 ± 5.174
210 {180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 1, 500, 0.1 · α _i }	2913.10 ± 18.061	2646.67 ± 18.262	2900.67 ± 21.175	2611.62 ± 15.147
211 {100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 1, 500, 0.1 · α _i }	1599.02 ± 6.236	1725.86 ± 7.249	1600.28 ± 8.962	1722.69 ± 12.920
212 {180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 1, 500, 0.1 · α _i }	3499.89 ± 20.299	3544.58 ± 23.749	3497.80 ± 22.386	3564.19 ± 18.534
213 {100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 1, 500, 0.1 · α _i }	811.50 ± 4.301	762.67 ± 2.974	839.00 ± 3.272	1093.99 ± 7.002
214 {180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 1, 500, 0.1 · α _i }	2839.21 ± 10.505	2418.95 ± 10.885	2862.43 ± 20.323	2402.17 ± 17.296
215 {100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ ¹ / ₁₀ · N ^d], U[0.01; 0.05], 1, 500, 0.1 · α _i }	1542.87 ± 7.097	1647.59 ± 7.414	1561.45 ± 7.339	1647.54 ± 10.709

Continued on next page

Table A.3: – continued from previous page

Instance $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$	Average cost per time unit and 95% confidence interval of heuristic n			
	1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R
216 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 1, 500, $0.1 \cdot \alpha_i$ }	3386.14 ± 16.931	3380.74 ± 20.284	3371.04 ± 22.923	3366.76 ± 17.507
217 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 1, 500, $0.1 \cdot \alpha_i$ }	222.32 ± 1.112	150.43 ± 0.978	342.87 ± 1.303	158.49 ± 0.650
218 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 1, 500, $0.1 \cdot \alpha_i$ }	713.36 ± 4.137	318.34 ± 1.687	1059.11 ± 5.190	324.25 ± 2.335
219 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 1, 500, $0.1 \cdot \alpha_i$ }	666.60 ± 3.400	177.52 ± 0.710	691.54 ± 4.772	183.61 ± 1.249
220 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 1, 500, $0.1 \cdot \alpha_i$ }	2457.19 ± 13.515	404.37 ± 2.911	2421.75 ± 15.741	395.48 ± 2.847
221 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 1, 500, $0.1 \cdot \alpha_i$ }	155.02 ± 0.651	58.03 ± 0.366	239.06 ± 1.650	75.60 ± 0.544
222 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 1, 500, $0.1 \cdot \alpha_i$ }	949.02 ± 4.176	118.21 ± 0.757	1540.57 ± 5.700	183.39 ± 1.009
223 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 1, 500, $0.1 \cdot \alpha_i$ }	632.82 ± 4.493	90.29 ± 0.433	910.62 ± 5.919	161.26 ± 1.048
224 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 1, 500, $0.1 \cdot \alpha_i$ }	2382.44 ± 9.768	242.74 ± 1.408	3003.03 ± 15.315	2819.88 ± 19.175
225 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	135.69 ± 0.651	76.39 ± 0.489	127.00 ± 0.521	73.00 ± 0.263
226 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	587.55 ± 2.997	184.95 ± 1.054	421.48 ± 2.276	182.76 ± 0.713
227 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	360.61 ± 1.947	141.18 ± 0.918	321.28 ± 1.221	143.00 ± 0.644
228 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	1834.08 ± 9.904	2429.47 ± 17.249	1806.94 ± 12.468	2440.92 ± 16.842
229 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	181.62 ± 1.308	59.06 ± 0.266	245.85 ± 1.106	732.88 ± 4.031
230 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	548.57 ± 2.469	98.65 ± 0.385	561.29 ± 2.863	95.52 ± 0.707
231 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	312.39 ± 1.156	98.29 ± 0.718	613.82 ± 3.990	1353.59 ± 6.362
232 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	1573.65 ± 6.137	2340.29 ± 15.914	1833.55 ± 8.801	2516.16 ± 17.865
233 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	66.12 ± 0.304	57.54 ± 0.207	73.21 ± 0.439	61.78 ± 0.216
234 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	147.12 ± 0.750	130.45 ± 0.952	148.19 ± 0.963	127.59 ± 0.536
235 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	82.94 ± 0.605	72.49 ± 0.536	82.39 ± 0.363	71.71 ± 0.516
236 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	220.76 ± 1.435	141.45 ± 0.665	202.68 ± 0.993	143.56 ± 1.019
237 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	48.12 ± 0.183	37.83 ± 0.257	43.73 ± 0.201	31.13 ± 0.140
238 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	74.06 ± 0.400	54.08 ± 0.357	83.53 ± 0.301	45.40 ± 0.250
239 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	45.95 ± 0.234	32.52 ± 0.205	53.93 ± 0.361	29.01 ± 0.215
240 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.001; 0.01]$, 4, 500, $0.1 \cdot \alpha_i$ }	276.61 ± 1.853	105.81 ± 0.466	199.70 ± 1.138	95.88 ± 0.537
241 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	1129.28 ± 8.470	1006.37 ± 4.730	1122.32 ± 5.050	1030.31 ± 3.812
242 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	2958.05 ± 17.453	2624.42 ± 15.222	2933.59 ± 20.535	2637.22 ± 19.252
243 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	1589.72 ± 6.995	1759.77 ± 12.142	1592.03 ± 8.756	1713.29 ± 9.594
244 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	3538.16 ± 22.290	3554.37 ± 22.393	3535.74 ± 18.386	3551.38 ± 17.402
245 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	987.85 ± 4.742	907.83 ± 5.992	961.03 ± 3.460	906.30 ± 3.806
246 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	2866.40 ± 10.606	2500.02 ± 14.750	2826.18 ± 11.587	2446.77 ± 18.351
247 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	1493.81 ± 8.515	1694.04 ± 6.437	1494.06 ± 5.976	1692.03 ± 7.953
248 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{1}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	3483.03 ± 13.236	3581.17 ± 22.561	3501.78 ± 17.859	3568.38 ± 17.842
249 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	263.22 ± 1.790	192.99 ± 0.830	334.60 ± 1.405	196.11 ± 1.039
250 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	1130.43 ± 6.217	357.94 ± 1.826	861.67 ± 4.308	386.65 ± 2.668
251 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	647.27 ± 2.848	213.74 ± 1.475	622.99 ± 3.551	216.20 ± 1.254
252 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	2557.59 ± 8.952	465.63 ± 3.259	2592.87 ± 10.371	483.01 ± 2.657
253 {100, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	177.15 ± 0.974	77.96 ± 0.405	395.56 ± 1.740	82.30 ± 0.354
254 {180, $(0.4 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	843.83 ± 5.907	159.08 ± 1.098	1341.95 ± 8.052	205.51 ± 1.151
255 {100, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	702.08 ± 2.949	133.46 ± 0.587	939.98 ± 5.828	232.70 ± 1.396
256 {180, $(0.6 \cdot \mathcal{N}^d)^2$, $[1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}]$, $[\frac{2}{10} \cdot \mathcal{N}^d]$, $U[0.01; 0.05]$, 4, 500, $0.1 \cdot \alpha_i$ }	2427.68 ± 9.225	304.55 ± 1.370	2590.73 ± 17.617	2065.43 ± 13.838

Table A.4: Average cost per time unit and 95% confidence interval for each instance of large symmetric test bed: heuristic 5-8

Instance $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$	Average cost per time unit and 95% confidence interval of heuristic n				
	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R	
1	{100, (0.4 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	48.11 ± 0.260	25.63 ± 0.118	39.02 ± 0.258	24.76 ± 0.156
2	{180, (0.4 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	125.84 ± 0.478	49.99 ± 0.290	104.21 ± 0.511	49.24 ± 0.207
3	{100, (0.6 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	70.42 ± 0.444	31.62 ± 0.221	65.93 ± 0.323	29.89 ± 0.111
4	{180, (0.6 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	132.59 ± 0.862	56.00 ± 0.353	130.48 ± 0.926	51.23 ± 0.205
5	{100, (0.4 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	26.96 ± 0.097	8.57 ± 0.058	23.20 ± 0.172	8.69 ± 0.047
6	{180, (0.4 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	106.30 ± 0.723	19.52 ± 0.080	86.92 ± 0.626	20.20 ± 0.117
7	{100, (0.6 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	49.58 ± 0.238	10.06 ± 0.066	45.37 ± 0.231	9.79 ± 0.048
8	{180, (0.6 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	107.70 ± 0.646	23.72 ± 0.157	106.31 ± 0.521	21.78 ± 0.076
9	{100, (0.4 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	25.98 ± 0.166	23.68 ± 0.135	27.53 ± 0.173	23.34 ± 0.100
10	{180, (0.4 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	54.11 ± 0.379	47.83 ± 0.282	54.19 ± 0.266	48.65 ± 0.190
11	{100, (0.6 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	25.85 ± 0.103	20.44 ± 0.096	26.03 ± 0.167	20.62 ± 0.111
12	{180, (0.6 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	57.64 ± 0.329	33.56 ± 0.178	51.67 ± 0.186	32.93 ± 0.234
13	{100, (0.4 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	21.62 ± 0.154	13.23 ± 0.077	14.88 ± 0.058	8.82 ± 0.034
14	{180, (0.4 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	37.91 ± 0.190	20.88 ± 0.121	30.56 ± 0.177	18.14 ± 0.125
15	{100, (0.6 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	19.87 ± 0.125	10.65 ± 0.067	15.20 ± 0.076	9.27 ± 0.065
16	{180, (0.6 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 1, 50, 0.05 · α _i }	42.66 ± 0.316	17.68 ± 0.131	32.72 ± 0.229	13.54 ± 0.083
17	{100, (0.4 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	144.21 ± 0.851	83.01 ± 0.382	145.88 ± 0.686	81.03 ± 0.340
18	{180, (0.4 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	262.23 ± 1.364	167.73 ± 1.241	261.50 ± 1.281	166.36 ± 0.799
19	{100, (0.6 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	146.50 ± 0.996	109.68 ± 0.592	147.39 ± 0.722	109.54 ± 0.822
20	{180, (0.6 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	252.16 ± 1.790	199.19 ± 1.394	251.39 ± 0.880	200.78 ± 1.365
21	{100, (0.4 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	125.80 ± 0.742	44.40 ± 0.333	128.00 ± 0.538	59.57 ± 0.226
22	{180, (0.4 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	209.17 ± 1.109	89.80 ± 0.404	210.29 ± 1.304	87.16 ± 0.523
23	{100, (0.6 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	115.79 ± 0.452	57.54 ± 0.236	114.52 ± 0.802	56.80 ± 0.267
24	{180, (0.6 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	202.52 ± 1.377	126.05 ± 0.920	217.31 ± 0.934	124.74 ± 0.574
25	{100, (0.4 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	89.32 ± 0.625	67.04 ± 0.429	101.50 ± 0.670	69.47 ± 0.347
26	{180, (0.4 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	238.65 ± 1.456	133.90 ± 0.683	197.32 ± 0.967	131.86 ± 0.633
27	{100, (0.6 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	147.08 ± 0.706	58.55 ± 0.351	117.05 ± 0.609	55.91 ± 0.268
28	{180, (0.6 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	287.13 ± 1.809	102.90 ± 0.617	287.70 ± 1.007	101.87 ± 0.621
29	{100, (0.4 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	34.90 ± 0.188	14.87 ± 0.062	51.57 ± 0.315	16.42 ± 0.092
30	{180, (0.4 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	229.26 ± 1.100	39.67 ± 0.159	223.41 ± 1.050	52.72 ± 0.274
31	{100, (0.6 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	132.37 ± 0.675	24.44 ± 0.093	130.58 ± 0.979	33.38 ± 0.130
32	{180, (0.6 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.01; 0.05], 1, 50, 0.05 · α _i }	248.64 ± 1.740	46.01 ± 0.235	243.13 ± 1.070	49.13 ± 0.300
33	{100, (0.4 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	55.58 ± 0.200	36.29 ± 0.265	54.70 ± 0.367	35.16 ± 0.239
34	{180, (0.4 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	161.12 ± 0.773	69.98 ± 0.462	125.20 ± 0.651	67.20 ± 0.249
35	{100, (0.6 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	95.49 ± 0.382	41.65 ± 0.275	88.37 ± 0.451	39.78 ± 0.199
36	{180, (0.6 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	181.49 ± 1.107	79.90 ± 0.304	181.90 ± 1.000	76.48 ± 0.497
37	{100, (0.4 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	66.04 ± 0.231	29.24 ± 0.158	62.43 ± 0.381	27.55 ± 0.201
38	{180, (0.4 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	149.72 ± 1.003	43.30 ± 0.234	123.85 ± 0.533	42.54 ± 0.217
39	{100, (0.6 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	83.46 ± 0.292	33.21 ± 0.156	77.05 ± 0.539	37.05 ± 0.267
40	{180, (0.6 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{1}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	163.17 ± 1.061	62.83 ± 0.302	158.55 ± 1.015	62.57 ± 0.419
41	{100, (0.4 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	31.40 ± 0.176	29.47 ± 0.121	34.01 ± 0.248	29.19 ± 0.155
42	{180, (0.4 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	62.21 ± 0.230	56.60 ± 0.402	66.28 ± 0.411	56.56 ± 0.249
43	{100, (0.6 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	33.57 ± 0.148	26.67 ± 0.147	34.54 ± 0.256	25.21 ± 0.141
44	{180, (0.6 · N ^d) ² , [1 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	97.25 ± 0.467	61.47 ± 0.234	81.80 ± 0.352	56.52 ± 0.322
45	{100, (0.4 · N ^d) ² , [1.5 · √(N /N), ⌊ $\frac{2}{10}$ · N ^d], U[0.001; 0.01], 4, 50, 0.05 · α _i }	42.58 ± 0.226	40.42 ± 0.158	22.47 ± 0.106	16.52 ± 0.088

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Table A.4: – continued from previous page

Instance $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$	Average cost per time unit and 95% confidence interval of heuristic n				
	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R	
46	{180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 50, 0.05 · α _i }	54.72 ± 0.263	38.12 ± 0.175	43.46 ± 0.178	29.80 ± 0.200
47	{100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 50, 0.05 · α _i }	27.63 ± 0.111	19.66 ± 0.088	28.23 ± 0.102	19.48 ± 0.068
48	{180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 50, 0.05 · α _i }	85.91 ± 0.369	52.53 ± 0.305	67.17 ± 0.322	39.53 ± 0.261
49	{100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	174.41 ± 0.977	107.10 ± 0.461	172.23 ± 1.206	102.36 ± 0.583
50	{180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	312.81 ± 2.158	214.12 ± 1.071	315.30 ± 1.387	217.73 ± 1.633
51	{100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	172.07 ± 0.602	133.24 ± 0.746	172.22 ± 1.137	130.37 ± 0.574
52	{180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	297.49 ± 1.874	247.73 ± 1.263	299.31 ± 2.005	248.53 ± 1.640
53	{100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	146.69 ± 0.865	58.37 ± 0.350	142.71 ± 0.756	56.44 ± 0.344
54	{180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	261.66 ± 1.099	129.53 ± 0.959	262.73 ± 1.340	131.10 ± 0.642
55	{100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	140.55 ± 0.520	82.07 ± 0.558	141.80 ± 0.567	83.79 ± 0.352
56	{180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	252.71 ± 1.440	175.69 ± 1.283	262.68 ± 1.944	178.51 ± 1.250
57	{100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	105.78 ± 0.635	81.91 ± 0.401	104.72 ± 0.482	81.78 ± 0.343
58	{180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	304.68 ± 2.102	163.53 ± 0.899	264.43 ± 1.666	161.31 ± 0.807
59	{100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	205.46 ± 1.418	86.88 ± 0.348	184.49 ± 1.125	86.54 ± 0.623
60	{180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	388.85 ± 2.800	164.79 ± 0.676	389.12 ± 1.401	159.65 ± 0.974
61	{100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	86.08 ± 0.344	43.72 ± 0.262	83.83 ± 0.578	46.49 ± 0.200
62	{180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	309.87 ± 2.045	86.10 ± 0.370	290.92 ± 1.949	87.84 ± 0.509
63	{100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	187.22 ± 1.311	63.68 ± 0.287	178.18 ± 1.283	67.26 ± 0.256
64	{180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 50, 0.05 · α _i }	353.25 ± 2.296	105.87 ± 0.413	333.78 ± 1.903	105.97 ± 0.657
65	{100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	97.89 ± 0.578	54.55 ± 0.398	86.56 ± 0.467	53.68 ± 0.252
66	{180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	268.09 ± 0.992	105.91 ± 0.561	229.10 ± 1.123	102.55 ± 0.615
67	{100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	141.21 ± 0.579	54.49 ± 0.229	129.52 ± 0.479	52.76 ± 0.216
68	{180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	304.55 ± 1.157	118.52 ± 0.640	304.08 ± 2.068	114.24 ± 0.457
69	{100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	81.97 ± 0.369	20.98 ± 0.076	94.51 ± 0.510	24.21 ± 0.155
70	{180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	242.16 ± 1.308	34.96 ± 0.220	250.57 ± 0.902	52.30 ± 0.194
71	{100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	121.25 ± 0.800	19.44 ± 0.140	114.35 ± 0.423	25.70 ± 0.093
72	{180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	232.82 ± 0.815	33.66 ± 0.121	230.94 ± 1.547	30.44 ± 0.174
73	{100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	68.73 ± 0.289	64.06 ± 0.429	71.46 ± 0.536	63.41 ± 0.342
74	{180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	113.67 ± 0.693	100.50 ± 0.613	116.27 ± 0.860	98.68 ± 0.454
75	{100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	76.12 ± 0.472	57.70 ± 0.421	75.55 ± 0.325	60.50 ± 0.254
76	{180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	128.58 ± 0.489	76.76 ± 0.422	106.55 ± 0.757	74.18 ± 0.341
77	{100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	23.22 ± 0.118	12.71 ± 0.078	31.02 ± 0.112	13.82 ± 0.087
78	{180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	43.12 ± 0.164	21.34 ± 0.092	43.46 ± 0.261	18.39 ± 0.066
79	{100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	13.67 ± 0.049	7.69 ± 0.031	22.63 ± 0.091	8.88 ± 0.065
80	{180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 500, 0.05 · α _i }	91.41 ± 0.658	24.37 ± 0.085	69.51 ± 0.500	22.60 ± 0.133
81	{100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	342.57 ± 1.644	198.45 ± 0.992	346.86 ± 1.249	199.12 ± 0.916
82	{180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	629.01 ± 4.277	405.21 ± 2.999	629.78 ± 3.779	401.77 ± 2.049
83	{100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	346.24 ± 2.458	249.55 ± 0.998	347.29 ± 2.084	246.20 ± 1.797
84	{180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	603.83 ± 2.355	472.57 ± 1.938	594.94 ± 3.986	472.13 ± 3.258
85	{100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	294.07 ± 1.294	97.99 ± 0.676	291.67 ± 2.012	160.72 ± 0.739
86	{180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	510.22 ± 2.092	221.18 ± 0.995	518.60 ± 2.697	219.11 ± 0.876
87	{100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	262.86 ± 1.314	122.62 ± 0.748	264.11 ± 1.426	115.04 ± 0.495
88	{180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	462.89 ± 3.194	265.31 ± 1.194	471.47 ± 3.159	267.95 ± 1.125
89	{100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	215.95 ± 1.555	143.02 ± 1.015	256.63 ± 1.745	154.32 ± 1.003
90	{180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	566.73 ± 4.194	300.50 ± 1.232	634.03 ± 3.107	305.28 ± 2.106
91	{100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	334.72 ± 2.209	140.84 ± 0.915	331.24 ± 1.259	135.67 ± 0.787

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Table A.4: – continued from previous page

		Average cost per time unit and 95% confidence interval of heuristic n			
Instance $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$					
	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R	
92	{180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	666.27 ± 4.531	219.93 ± 0.858	663.04 ± 2.785	226.77 ± 1.111
93	{100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	153.51 ± 0.768	51.96 ± 0.358	236.32 ± 1.512	62.96 ± 0.346
94	{180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	427.81 ± 2.567	66.01 ± 0.277	593.73 ± 2.731	93.06 ± 0.503
95	{100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	292.28 ± 1.169	42.89 ± 0.287	310.29 ± 1.614	59.92 ± 0.288
96	{180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 1, 500, 0.05 · α _i }	580.29 ± 2.495	73.54 ± 0.316	575.95 ± 2.880	91.92 ± 0.331
97	{100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	124.89 ± 0.674	64.91 ± 0.422	109.52 ± 0.745	63.54 ± 0.311
98	{180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	325.43 ± 2.083	135.61 ± 0.502	301.66 ± 1.237	131.45 ± 0.960
99	{100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	172.17 ± 0.826	69.28 ± 0.360	157.09 ± 0.958	66.44 ± 0.492
100	{180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	354.34 ± 2.587	147.94 ± 0.828	353.60 ± 1.839	140.18 ± 0.897
101	{100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	122.14 ± 0.684	38.45 ± 0.269	118.49 ± 0.746	41.10 ± 0.222
102	{180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	250.31 ± 1.552	54.26 ± 0.358	234.59 ± 1.290	57.24 ± 0.355
103	{100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	136.78 ± 0.602	33.64 ± 0.145	136.04 ± 0.748	37.89 ± 0.231
104	{180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	301.31 ± 2.109	73.75 ± 0.324	301.79 ± 1.630	73.57 ± 0.441
105	{100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	69.87 ± 0.279	64.39 ± 0.477	75.36 ± 0.535	66.15 ± 0.324
106	{180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	141.69 ± 0.581	124.51 ± 0.523	144.14 ± 0.793	125.84 ± 0.654
107	{100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	88.15 ± 0.309	63.34 ± 0.310	77.74 ± 0.498	59.46 ± 0.262
108	{180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	158.85 ± 0.921	102.54 ± 0.564	157.44 ± 0.819	103.96 ± 0.665
109	{100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	36.84 ± 0.225	28.31 ± 0.113	72.49 ± 0.486	21.38 ± 0.081
110	{180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	66.95 ± 0.449	46.09 ± 0.244	74.20 ± 0.527	36.14 ± 0.260
111	{100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	46.98 ± 0.188	26.23 ± 0.163	70.50 ± 0.458	25.94 ± 0.182
112	{180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 4, 500, 0.05 · α _i }	292.61 ± 1.492	90.27 ± 0.487	224.57 ± 1.145	70.24 ± 0.372
113	{100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	379.40 ± 1.631	221.33 ± 1.107	374.27 ± 2.133	225.73 ± 1.467
114	{180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	681.59 ± 3.135	459.55 ± 2.528	680.90 ± 4.630	464.13 ± 1.671
115	{100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	371.66 ± 2.639	262.26 ± 1.338	371.45 ± 2.117	262.30 ± 1.784
116	{180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	656.96 ± 4.205	533.68 ± 1.975	657.84 ± 2.763	533.45 ± 2.454
117	{100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	306.16 ± 1.837	103.97 ± 0.655	313.63 ± 1.380	161.68 ± 0.711
118	{180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	553.51 ± 3.155	232.46 ± 1.348	553.41 ± 2.490	240.27 ± 1.586
119	{100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	290.26 ± 1.829	149.91 ± 0.600	292.04 ± 1.577	146.72 ± 0.983
120	{180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	541.85 ± 3.089	357.30 ± 2.394	540.29 ± 1.891	360.74 ± 1.623
121	{100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	207.31 ± 0.995	160.63 ± 0.916	337.56 ± 1.654	165.37 ± 1.174
122	{180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	600.88 ± 2.163	325.28 ± 2.310	588.56 ± 4.414	329.97 ± 1.485
123	{100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	402.11 ± 2.815	177.34 ± 1.117	387.98 ± 2.832	175.47 ± 1.281
124	{180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	764.92 ± 5.354	282.32 ± 1.440	762.25 ± 3.278	283.20 ± 1.586
125	{100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	118.53 ± 0.818	58.25 ± 0.239	282.35 ± 1.722	62.32 ± 0.355
126	{180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	513.66 ± 2.825	113.56 ± 0.693	674.69 ± 5.060	137.39 ± 0.866
127	{100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	341.76 ± 1.845	71.50 ± 0.472	349.44 ± 1.223	80.81 ± 0.388
128	{180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.01; 0.05], 4, 500, 0.05 · α _i }	669.67 ± 3.817	136.81 ± 0.903	649.77 ± 4.743	148.99 ± 0.849
129	{100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 50, 0.1 · α _i }	54.32 ± 0.375	27.68 ± 0.116	47.80 ± 0.325	27.84 ± 0.200
130	{180, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 50, 0.1 · α _i }	178.79 ± 1.180	49.04 ± 0.201	123.33 ± 0.444	47.45 ± 0.294
131	{100, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 50, 0.1 · α _i }	109.28 ± 0.787	28.81 ± 0.124	96.79 ± 0.465	28.52 ± 0.100
132	{180, (0.6 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 50, 0.1 · α _i }	239.44 ± 1.413	56.65 ± 0.266	239.95 ± 1.032	55.74 ± 0.268
133	{100, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 50, 0.1 · α _i }	62.96 ± 0.472	13.60 ± 0.057	61.48 ± 0.418	18.29 ± 0.073
134	{180, (0.4 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 50, 0.1 · α _i }	147.45 ± 0.575	18.78 ± 0.109	124.46 ± 0.784	21.31 ± 0.121
135	{100, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 50, 0.1 · α _i }	91.36 ± 0.566	15.11 ± 0.107	89.52 ± 0.358	18.02 ± 0.068
136	{180, (0.6 · N ^d) ² , [1.5 · √(N /N)], ⌊ $\frac{1}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 50, 0.1 · α _i }	181.95 ± 0.637	24.45 ± 0.176	182.01 ± 1.074	24.68 ± 0.168
137	{100, (0.4 · N ^d) ² , [1 · √(N /N)], ⌊ $\frac{2}{10}$ · N ^d ⌋, U[0.001; 0.01], 1, 50, 0.1 · α _i }	29.77 ± 0.199	27.68 ± 0.180	30.72 ± 0.144	28.51 ± 0.154

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Table A.4: – continued from previous page

Instance $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$	Average cost per time unit and 95% confidence interval of heuristic n			
	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
138 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.1 \cdot \alpha_i\}$	52.81 ± 0.312	44.75 ± 0.161	56.02 ± 0.202	45.53 ± 0.219
139 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.1 \cdot \alpha_i\}$	39.77 ± 0.183	26.60 ± 0.184	34.22 ± 0.222	25.51 ± 0.094
140 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.1 \cdot \alpha_i\}$	52.62 ± 0.284	32.07 ± 0.218	49.92 ± 0.265	31.81 ± 0.204
141 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.1 \cdot \alpha_i\}$	12.38 ± 0.063	8.32 ± 0.035	9.36 ± 0.049	5.67 ± 0.042
142 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.1 \cdot \alpha_i\}$	42.28 ± 0.266	22.39 ± 0.150	31.50 ± 0.220	15.95 ± 0.083
143 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.1 \cdot \alpha_i\}$	10.45 ± 0.073	6.67 ± 0.039	10.91 ± 0.082	6.17 ± 0.043
144 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.1 \cdot \alpha_i\}$	44.47 ± 0.311	15.37 ± 0.088	31.11 ± 0.140	14.17 ± 0.105
145 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	196.22 ± 0.883	90.98 ± 0.646	194.43 ± 0.933	89.38 ± 0.518
146 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	392.37 ± 2.825	212.95 ± 1.129	393.45 ± 2.518	203.11 ± 0.853
147 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	233.66 ± 1.636	148.80 ± 0.655	234.27 ± 1.570	146.60 ± 0.718
148 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	435.68 ± 2.658	322.72 ± 2.259	437.26 ± 2.580	317.55 ± 2.350
149 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	156.35 ± 0.876	40.49 ± 0.190	156.20 ± 1.015	53.15 ± 0.260
150 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	292.81 ± 1.552	92.58 ± 0.398	293.68 ± 1.762	93.23 ± 0.475
151 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	170.74 ± 1.281	71.74 ± 0.337	198.53 ± 0.814	98.51 ± 0.729
152 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	338.49 ± 2.065	191.94 ± 0.960	334.01 ± 1.637	195.67 ± 1.057
153 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	95.68 ± 0.679	67.71 ± 0.318	97.54 ± 0.585	69.53 ± 0.521
154 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	272.22 ± 1.307	133.50 ± 0.681	213.44 ± 1.537	132.13 ± 0.687
155 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	228.11 ± 1.209	68.94 ± 0.421	161.40 ± 1.178	67.08 ± 0.463
156 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	502.35 ± 2.462	116.01 ± 0.789	499.79 ± 2.199	112.33 ± 0.472
157 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	65.52 ± 0.373	17.98 ± 0.070	62.45 ± 0.375	22.33 ± 0.143
158 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	290.99 ± 1.775	40.93 ± 0.147	276.04 ± 1.021	49.10 ± 0.280
159 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	183.58 ± 1.285	26.28 ± 0.187	181.75 ± 1.181	33.89 ± 0.227
160 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.1 \cdot \alpha_i\}$	416.07 ± 1.498	47.61 ± 0.309	398.12 ± 1.792	57.50 ± 0.288
161 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	67.64 ± 0.440	32.30 ± 0.126	57.07 ± 0.348	32.03 ± 0.144
162 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	207.46 ± 1.328	64.47 ± 0.361	140.40 ± 0.660	62.47 ± 0.362
163 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	123.22 ± 0.567	42.13 ± 0.211	106.92 ± 0.428	40.99 ± 0.205
164 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	293.03 ± 1.788	91.10 ± 0.683	295.24 ± 1.033	87.31 ± 0.471
165 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	79.22 ± 0.404	27.76 ± 0.136	70.27 ± 0.513	26.31 ± 0.103
166 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	213.68 ± 1.047	45.09 ± 0.171	198.00 ± 1.089	43.39 ± 0.282
167 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	107.40 ± 0.795	29.08 ± 0.183	103.26 ± 0.372	31.33 ± 0.160
168 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	239.91 ± 1.176	63.32 ± 0.393	237.86 ± 1.023	60.48 ± 0.242
169 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	45.21 ± 0.231	38.97 ± 0.238	38.90 ± 0.194	35.89 ± 0.133
170 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	65.73 ± 0.394	56.62 ± 0.209	70.58 ± 0.423	56.21 ± 0.225
171 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	36.06 ± 0.206	29.39 ± 0.215	37.43 ± 0.191	29.66 ± 0.154
172 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	109.30 ± 0.590	62.64 ± 0.370	85.17 ± 0.383	53.93 ± 0.237
173 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	13.27 ± 0.082	11.10 ± 0.051	16.02 ± 0.093	10.96 ± 0.069
174 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	83.53 ± 0.376	62.89 ± 0.459	52.73 ± 0.295	32.35 ± 0.181
175 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	39.80 ± 0.251	27.84 ± 0.142	29.92 ± 0.168	18.80 ± 0.115
176 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.1 \cdot \alpha_i\}$	94.19 ± 0.593	50.70 ± 0.218	76.55 ± 0.452	41.10 ± 0.251
177 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	223.38 ± 0.782	111.20 ± 0.589	223.70 ± 0.828	113.18 ± 0.453
178 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	444.36 ± 2.977	264.99 ± 1.537	441.69 ± 2.341	264.87 ± 1.086
179 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	256.18 ± 1.921	165.86 ± 1.178	259.05 ± 1.243	171.96 ± 0.671
180 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	478.19 ± 1.769	352.63 ± 1.622	478.58 ± 2.632	355.84 ± 1.886
181 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	179.89 ± 0.953	60.05 ± 0.360	184.94 ± 0.962	110.19 ± 0.408
182 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	343.89 ± 1.754	148.69 ± 0.743	346.28 ± 1.835	148.89 ± 0.759
183 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	194.83 ± 1.188	92.98 ± 0.604	204.85 ± 0.983	156.14 ± 0.609

Continued on next page

Table A.4: – continued from previous page

Instance $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$	Average cost per time unit and 95% confidence interval of heuristic n			
	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
184 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	376.32 ± 2.559	231.68 ± 0.880	380.96 ± 2.743	229.08 ± 0.985
185 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	101.16 ± 0.364	75.83 ± 0.349	105.43 ± 0.696	75.75 ± 0.439
186 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	367.83 ± 2.464	168.99 ± 0.997	271.84 ± 2.012	168.14 ± 0.639
187 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	255.26 ± 1.302	80.26 ± 0.417	179.80 ± 1.295	76.37 ± 0.512
188 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	612.46 ± 2.940	173.30 ± 0.797	589.27 ± 3.241	174.84 ± 1.119
189 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	64.60 ± 0.297	35.28 ± 0.152	76.63 ± 0.330	40.23 ± 0.237
190 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	405.36 ± 2.351	89.20 ± 0.660	444.92 ± 2.625	91.61 ± 0.330
191 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	235.71 ± 1.202	52.97 ± 0.254	233.12 ± 1.282	53.64 ± 0.290
192 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.1 \cdot \alpha_i\}$	518.25 ± 3.887	110.06 ± 0.605	495.14 ± 2.971	110.00 ± 0.693
193 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	143.51 ± 0.517	73.33 ± 0.477	126.78 ± 0.710	72.84 ± 0.408
194 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	398.21 ± 2.389	107.12 ± 0.557	258.27 ± 1.240	102.96 ± 0.607
195 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	252.07 ± 1.714	68.46 ± 0.486	210.82 ± 1.328	66.95 ± 0.355
196 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	562.46 ± 3.037	131.90 ± 0.699	557.66 ± 1.952	124.78 ± 0.811
197 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	56.60 ± 0.283	12.19 ± 0.051	74.25 ± 0.401	11.99 ± 0.068
198 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	379.37 ± 1.745	30.35 ± 0.106	370.31 ± 2.037	36.62 ± 0.238
199 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	187.46 ± 1.237	24.29 ± 0.172	186.03 ± 1.172	23.20 ± 0.123
200 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	425.60 ± 2.128	42.93 ± 0.275	420.80 ± 2.946	39.36 ± 0.216
201 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	57.69 ± 0.306	51.14 ± 0.292	61.92 ± 0.223	50.63 ± 0.329
202 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	138.50 ± 0.734	118.23 ± 0.698	140.36 ± 0.926	118.81 ± 0.547
203 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	50.49 ± 0.237	39.18 ± 0.208	53.01 ± 0.223	40.15 ± 0.281
204 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	137.78 ± 0.951	77.23 ± 0.502	127.88 ± 0.857	78.27 ± 0.485
205 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	26.17 ± 0.126	16.16 ± 0.116	34.76 ± 0.212	17.23 ± 0.098
206 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	49.92 ± 0.329	23.91 ± 0.148	68.47 ± 0.288	25.22 ± 0.126
207 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	33.85 ± 0.213	14.47 ± 0.071	53.57 ± 0.332	14.99 ± 0.060
208 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i\}$	101.32 ± 0.476	22.07 ± 0.150	77.35 ± 0.503	22.62 ± 0.120
209 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	483.91 ± 2.129	220.60 ± 1.103	481.24 ± 1.732	214.49 ± 0.922
210 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	952.37 ± 3.333	506.76 ± 3.446	952.09 ± 5.713	509.44 ± 2.904
211 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	556.89 ± 3.954	339.43 ± 1.290	558.44 ± 2.513	331.87 ± 2.091
212 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	1015.36 ± 6.803	714.08 ± 3.356	1036.72 ± 7.568	709.92 ± 4.402
213 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	369.86 ± 2.589	88.85 ± 0.560	381.67 ± 1.756	122.23 ± 0.794
214 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	726.20 ± 3.631	224.07 ± 1.681	721.52 ± 5.267	225.17 ± 1.689
215 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	417.95 ± 1.546	179.15 ± 0.734	465.45 ± 2.607	252.45 ± 1.136
216 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	744.55 ± 2.829	383.71 ± 2.417	794.67 ± 4.132	374.37 ± 1.535
217 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	215.38 ± 0.797	143.23 ± 1.003	326.80 ± 1.144	150.36 ± 0.647
218 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	669.00 ± 4.884	289.76 ± 2.173	856.94 ± 3.171	295.03 ± 1.623
219 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	550.84 ± 3.085	139.27 ± 0.836	577.89 ± 2.658	149.20 ± 1.059
220 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	1209.81 ± 5.202	261.73 ± 1.152	1198.37 ± 6.951	255.01 ± 1.811
221 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	151.79 ± 0.911	42.68 ± 0.213	238.24 ± 0.953	58.94 ± 0.224
222 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	680.42 ± 3.062	70.20 ± 0.498	895.33 ± 4.119	102.36 ± 0.543
223 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	470.16 ± 2.492	49.08 ± 0.260	492.91 ± 3.549	72.95 ± 0.445
224 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i\}$	995.65 ± 7.368	93.32 ± 0.532	901.45 ± 4.417	203.06 ± 1.320
225 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	136.73 ± 0.697	62.10 ± 0.286	129.74 ± 0.830	61.90 ± 0.279
226 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	466.03 ± 2.004	149.13 ± 1.044	390.54 ± 1.523	143.18 ± 0.745
227 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	287.00 ± 1.292	91.86 ± 0.340	265.26 ± 1.989	84.31 ± 0.304
228 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	631.38 ± 2.273	175.62 ± 1.089	620.02 ± 4.278	165.96 ± 1.195
229 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	166.89 ± 0.668	47.58 ± 0.257	183.54 ± 0.771	65.17 ± 0.332

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Table A.4: – continued from previous page

Instance $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$	Average cost per time unit and 95% confidence interval of heuristic n			
	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
230 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	404.16 ± 2.061	52.38 ± 0.251	347.79 ± 1.739	54.02 ± 0.297
231 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	220.12 ± 1.321	46.49 ± 0.246	229.89 ± 1.632	61.57 ± 0.252
232 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	466.78 ± 2.381	75.13 ± 0.398	454.53 ± 2.227	93.33 ± 0.504
233 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	64.99 ± 0.266	57.44 ± 0.236	76.31 ± 0.305	60.18 ± 0.439
234 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	143.14 ± 0.601	119.32 ± 0.752	149.56 ± 0.987	123.08 ± 0.886
235 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	81.05 ± 0.559	66.18 ± 0.351	82.34 ± 0.305	65.99 ± 0.271
236 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	218.19 ± 1.418	124.40 ± 0.610	192.66 ± 0.828	119.59 ± 0.706
237 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	47.73 ± 0.167	33.94 ± 0.139	42.95 ± 0.159	26.86 ± 0.175
238 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	71.34 ± 0.321	47.21 ± 0.194	81.34 ± 0.455	37.51 ± 0.154
239 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	49.10 ± 0.363	24.32 ± 0.136	50.99 ± 0.331	22.17 ± 0.126
240 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i\}$	242.87 ± 1.579	89.26 ± 0.544	181.69 ± 1.072	62.30 ± 0.424
241 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	533.54 ± 3.628	253.58 ± 0.964	531.93 ± 2.660	254.47 ± 1.221
242 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	998.80 ± 5.693	534.41 ± 3.474	999.15 ± 5.096	525.76 ± 3.155
243 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	577.45 ± 2.483	348.36 ± 2.543	574.21 ± 4.249	350.50 ± 1.437
244 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	1064.26 ± 6.173	744.29 ± 5.508	1071.99 ± 6.432	749.02 ± 4.869
245 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	408.53 ± 1.552	105.85 ± 0.476	406.78 ± 2.278	114.88 ± 0.448
246 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	762.97 ± 2.747	265.72 ± 1.541	767.17 ± 4.373	264.24 ± 1.744
247 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	427.40 ± 2.906	182.71 ± 0.932	422.47 ± 2.915	172.26 ± 1.292
248 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	895.43 ± 5.283	529.47 ± 2.065	883.47 ± 4.594	513.36 ± 3.799
249 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	255.54 ± 1.789	183.17 ± 1.007	330.17 ± 2.245	187.82 ± 1.089
250 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	862.27 ± 3.104	334.48 ± 2.274	737.16 ± 4.644	345.99 ± 1.903
251 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	576.21 ± 3.169	171.60 ± 0.961	544.61 ± 2.396	171.54 ± 0.841
252 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	1312.57 ± 7.088	302.26 ± 1.662	1312.71 ± 6.957	306.44 ± 1.073
253 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	176.47 ± 0.635	60.69 ± 0.449	372.17 ± 2.010	65.78 ± 0.283
254 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	615.95 ± 4.004	114.20 ± 0.856	977.31 ± 5.180	143.89 ± 0.676
255 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	522.50 ± 2.717	89.57 ± 0.493	542.86 ± 2.280	120.40 ± 0.710
256 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	1078.46 ± 5.500	149.60 ± 0.898	1051.05 ± 3.784	193.10 ± 0.734

Table A.5: Average cost per time unit and 95% confidence interval for each instance of large asymmetric test bed: heuristic 1-4

Instance ^a $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$	Average cost per time unit and 95% confidence interval of heuristic n			
	1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R
1 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i\}$	22.12 ± 0.086	12.09 ± 0.091	17.85 ± 0.130	12.39 ± 0.066
2 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i\}$	59.24 ± 0.243	23.84 ± 0.162	47.82 ± 0.273	23.09 ± 0.152
3 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i\}$	32.99 ± 0.208	18.70 ± 0.071	30.85 ± 0.213	19.76 ± 0.122
4 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i\}$	88.72 ± 0.435	104.96 ± 0.577	90.95 ± 0.437	105.96 ± 0.689
5 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i\}$	16.59 ± 0.105	7.42 ± 0.055	12.93 ± 0.066	7.19 ± 0.047
6 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i\}$	48.55 ± 0.252	14.04 ± 0.105	32.37 ± 0.214	13.02 ± 0.090
7 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i\}$	28.48 ± 0.205	12.92 ± 0.089	40.42 ± 0.299	58.54 ± 0.340
8 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i\}$	84.19 ± 0.446	101.44 ± 0.680	83.35 ± 0.475	101.10 ± 0.677
9 $\{100, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i\}$	10.85 ± 0.049	10.24 ± 0.065	11.16 ± 0.057	10.06 ± 0.057
10 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i\}$	22.37 ± 0.078	20.32 ± 0.089	22.52 ± 0.095	20.75 ± 0.131
11 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i\}$	11.71 ± 0.052	9.38 ± 0.070	11.65 ± 0.052	9.35 ± 0.056
12 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i\}$	29.69 ± 0.146	20.02 ± 0.114	25.86 ± 0.186	18.70 ± 0.138

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Table A.5: – continued from previous page

Instance ^a { $ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i$ }		Average cost per time unit and 95% confidence interval of heuristic n			
		1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R
13	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i$ }	7.03 ± 0.034	5.69 ± 0.023	5.16 ± 0.037	4.42 ± 0.019
14	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i$ }	17.06 ± 0.073	12.43 ± 0.060	12.26 ± 0.053	9.13 ± 0.038
15	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i$ }	13.82 ± 0.084	8.69 ± 0.033	11.12 ± 0.079	7.41 ± 0.027
16	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 50, 0.05 \cdot \alpha_i$ }	30.63 ± 0.126	17.33 ± 0.121	21.58 ± 0.086	14.25 ± 0.100
17	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	67.87 ± 0.394	61.74 ± 0.389	67.73 ± 0.440	59.83 ± 0.233
18	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	133.04 ± 0.865	127.06 ± 0.661	131.70 ± 0.843	126.07 ± 0.782
19	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	71.53 ± 0.472	72.15 ± 0.469	71.31 ± 0.492	71.99 ± 0.482
20	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	142.94 ± 0.643	140.86 ± 0.507	142.35 ± 1.053	141.15 ± 1.016
21	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	65.99 ± 0.475	52.75 ± 0.285	65.76 ± 0.355	55.08 ± 0.369
22	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	133.40 ± 0.760	123.19 ± 0.751	134.97 ± 0.567	126.07 ± 0.567
23	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	74.09 ± 0.289	74.31 ± 0.394	74.40 ± 0.298	74.47 ± 0.410
24	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	139.71 ± 0.880	136.67 ± 0.574	139.47 ± 0.879	137.12 ± 0.740
25	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	40.99 ± 0.213	31.55 ± 0.145	37.77 ± 0.212	31.04 ± 0.214
26	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	132.55 ± 0.464	58.94 ± 0.342	82.74 ± 0.364	58.18 ± 0.221
27	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	74.74 ± 0.448	33.08 ± 0.202	69.69 ± 0.467	34.61 ± 0.225
28	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	149.18 ± 0.746	69.27 ± 0.339	147.84 ± 1.094	69.35 ± 0.478
29	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	26.40 ± 0.182	13.32 ± 0.077	21.76 ± 0.118	13.17 ± 0.059
30	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	119.26 ± 0.751	32.34 ± 0.136	131.94 ± 0.528	34.85 ± 0.237
31	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	69.69 ± 0.272	23.07 ± 0.145	73.47 ± 0.470	58.27 ± 0.245
32	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 50, 0.05 \cdot \alpha_i$ }	142.16 ± 0.668	46.34 ± 0.227	142.14 ± 1.023	52.27 ± 0.382
33	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	42.40 ± 0.212	21.36 ± 0.096	33.69 ± 0.212	20.62 ± 0.099
34	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	110.83 ± 0.809	50.45 ± 0.187	91.81 ± 0.367	48.26 ± 0.212
35	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	59.68 ± 0.340	33.93 ± 0.234	55.08 ± 0.292	33.39 ± 0.200
36	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	145.76 ± 0.598	158.28 ± 0.696	147.02 ± 0.956	158.04 ± 0.553
37	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	29.90 ± 0.129	17.44 ± 0.127	24.86 ± 0.139	17.28 ± 0.062
38	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	103.63 ± 0.653	45.07 ± 0.212	85.31 ± 0.495	43.16 ± 0.285
39	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	57.96 ± 0.417	33.71 ± 0.199	58.71 ± 0.247	70.69 ± 0.269
40	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	141.47 ± 0.962	156.11 ± 1.124	142.64 ± 0.999	152.99 ± 1.056
41	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	14.90 ± 0.067	14.42 ± 0.088	16.16 ± 0.120	14.79 ± 0.108
42	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	37.87 ± 0.280	33.87 ± 0.159	40.54 ± 0.219	34.23 ± 0.164
43	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	23.14 ± 0.086	19.57 ± 0.135	22.65 ± 0.113	19.46 ± 0.086
44	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	82.55 ± 0.297	56.16 ± 0.399	60.60 ± 0.394	45.48 ± 0.291
45	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	17.60 ± 0.111	15.86 ± 0.113	12.52 ± 0.055	10.98 ± 0.067
46	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	43.99 ± 0.312	37.40 ± 0.131	33.39 ± 0.134	28.49 ± 0.182
47	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	29.69 ± 0.119	22.18 ± 0.087	23.67 ± 0.178	18.50 ± 0.083
48	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 50, 0.05 \cdot \alpha_i$ }	141.93 ± 0.908	91.48 ± 0.366	117.85 ± 0.754	56.51 ± 0.362
49	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i$ }	98.70 ± 0.701	91.87 ± 0.441	98.15 ± 0.667	89.65 ± 0.493
50	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i$ }	184.97 ± 0.906	178.95 ± 1.163	185.82 ± 1.115	179.21 ± 1.147
51	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i$ }	103.50 ± 0.724	104.01 ± 0.603	103.31 ± 0.362	103.64 ± 0.363
52	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i$ }	194.85 ± 1.247	192.26 ± 0.865	194.56 ± 0.934	192.18 ± 1.211
53	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i$ }	92.66 ± 0.361	78.34 ± 0.423	93.41 ± 0.654	79.81 ± 0.327
54	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i$ }	181.14 ± 0.942	171.73 ± 1.219	181.57 ± 1.126	171.37 ± 0.857
55	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i$ }	97.12 ± 0.437	99.68 ± 0.568	97.63 ± 0.596	94.18 ± 0.678
56	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i$ }	187.80 ± 1.221	185.26 ± 0.778	187.31 ± 0.693	184.83 ± 1.127
57	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i$ }	62.68 ± 0.301	42.61 ± 0.222	56.76 ± 0.358	43.13 ± 0.173
58	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 50, 0.05 \cdot \alpha_i$ }	178.29 ± 0.660	96.86 ± 0.436	131.17 ± 0.944	94.12 ± 0.574

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Table A.5: – continued from previous page

Instance ^a { $ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i$ }		Average cost per time unit and 95% confidence interval of heuristic n			
		1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R
59	{100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	122.89 ± 0.627	58.25 ± 0.256	91.77 ± 0.578	55.58 ± 0.300
60	{180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	252.80 ± 1.036	125.71 ± 0.817	253.38 ± 1.875	130.51 ± 0.966
61	{100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	47.01 ± 0.235	29.25 ± 0.167	42.23 ± 0.165	28.92 ± 0.124
62	{180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	225.13 ± 1.261	87.47 ± 0.490	223.32 ± 0.782	84.08 ± 0.496
63	{100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	127.06 ± 0.572	55.07 ± 0.380	124.36 ± 0.783	53.77 ± 0.242
64	{180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	248.81 ± 1.070	130.57 ± 0.496	226.86 ± 1.316	220.64 ± 1.258
65	{100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	71.16 ± 0.377	42.78 ± 0.218	62.75 ± 0.314	42.42 ± 0.161
66	{180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	184.88 ± 0.998	80.87 ± 0.485	144.13 ± 0.937	78.33 ± 0.470
67	{100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	98.26 ± 0.521	53.70 ± 0.295	93.57 ± 0.702	48.46 ± 0.170
68	{180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	325.84 ± 1.597	390.78 ± 2.579	334.44 ± 2.207	391.74 ± 2.742
69	{100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	49.33 ± 0.340	22.17 ± 0.113	47.63 ± 0.243	21.73 ± 0.091
70	{180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	174.44 ± 0.959	38.72 ± 0.205	135.51 ± 0.542	41.82 ± 0.151
71	{100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	91.65 ± 0.348	31.54 ± 0.192	80.83 ± 0.558	32.36 ± 0.220
72	{180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	319.15 ± 1.596	361.09 ± 1.950	323.24 ± 1.293	359.44 ± 2.085
73	{100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	35.87 ± 0.226	31.78 ± 0.175	37.52 ± 0.236	33.69 ± 0.179
74	{180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	90.78 ± 0.390	79.55 ± 0.374	91.15 ± 0.401	79.46 ± 0.397
75	{100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	40.42 ± 0.267	32.59 ± 0.124	39.71 ± 0.210	33.45 ± 0.137
76	{180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	95.15 ± 0.561	58.74 ± 0.235	82.26 ± 0.494	59.45 ± 0.434
77	{100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	13.47 ± 0.096	10.51 ± 0.054	11.52 ± 0.073	8.65 ± 0.032
78	{180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	65.12 ± 0.339	39.40 ± 0.197	42.80 ± 0.317	29.19 ± 0.149
79	{100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	24.29 ± 0.102	14.26 ± 0.081	21.56 ± 0.151	14.02 ± 0.065
80	{180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	70.99 ± 0.419	29.25 ± 0.184	54.26 ± 0.195	32.86 ± 0.214
81	{100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	243.07 ± 0.875	225.58 ± 1.647	241.91 ± 0.871	217.52 ± 1.240
82	{180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	493.60 ± 3.159	463.88 ± 3.433	497.47 ± 2.686	462.07 ± 2.357
83	{100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	276.26 ± 1.740	277.53 ± 1.776	274.24 ± 1.508	277.08 ± 1.662
84	{180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	530.21 ± 3.022	522.00 ± 2.088	528.47 ± 2.695	523.62 ± 3.456
85	{100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	249.14 ± 1.395	229.98 ± 1.311	251.97 ± 1.235	230.62 ± 1.107
86	{180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	464.87 ± 3.440	420.57 ± 1.682	469.56 ± 3.381	436.58 ± 1.659
87	{100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	270.30 ± 1.270	269.84 ± 1.160	264.88 ± 0.927	265.95 ± 1.755
88	{180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	530.33 ± 3.500	515.04 ± 2.009	530.91 ± 2.177	519.65 ± 2.131
89	{100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	136.37 ± 0.614	108.08 ± 0.400	143.93 ± 0.979	111.41 ± 0.624
90	{180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	362.90 ± 2.032	210.53 ± 1.516	296.43 ± 1.897	204.85 ± 1.434
91	{100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	229.40 ± 1.353	98.36 ± 0.452	232.69 ± 1.303	100.91 ± 0.656
92	{180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	471.67 ± 2.406	194.15 ± 1.068	478.28 ± 3.491	184.88 ± 1.146
93	{100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	162.68 ± 0.732	53.35 ± 0.331	200.43 ± 1.343	83.01 ± 0.315
94	{180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	375.03 ± 2.100	78.19 ± 0.414	450.49 ± 2.883	100.52 ± 0.392
95	{100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	197.63 ± 1.047	44.73 ± 0.309	171.50 ± 0.960	44.78 ± 0.215
96	{180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	460.50 ± 2.487	107.38 ± 0.387	459.95 ± 2.254	101.76 ± 0.448
97	{100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	90.61 ± 0.670	55.97 ± 0.196	81.03 ± 0.486	53.08 ± 0.387
98	{180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	271.50 ± 1.466	119.02 ± 0.607	239.51 ± 1.365	116.09 ± 0.836
99	{100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	141.00 ± 0.564	85.71 ± 0.523	141.04 ± 0.592	90.05 ± 0.567
100	{180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	375.72 ± 2.179	421.73 ± 1.856	378.86 ± 2.500	426.49 ± 2.303
101	{100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	77.87 ± 0.288	33.98 ± 0.238	83.96 ± 0.470	35.60 ± 0.242
102	{180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	229.76 ± 1.310	68.24 ± 0.423	201.77 ± 0.807	68.05 ± 0.327
103	{100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	105.94 ± 0.593	41.81 ± 0.238	96.68 ± 0.358	40.43 ± 0.158
104	{180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	339.67 ± 1.630	386.71 ± 2.630	346.28 ± 1.212	388.03 ± 2.483

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Table A.5: – continued from previous page

Instance ^a { $ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i$ }		Average cost per time unit and 95% confidence interval of heuristic n			
		1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R
105	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	38.35 ± 0.165	36.51 ± 0.193	41.79 ± 0.267	37.54 ± 0.248
106	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	100.65 ± 0.473	92.65 ± 0.593	102.23 ± 0.705	93.63 ± 0.571
107	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	42.31 ± 0.271	36.46 ± 0.179	45.63 ± 0.274	37.07 ± 0.267
108	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	119.69 ± 0.598	77.13 ± 0.363	101.57 ± 0.630	73.87 ± 0.443
109	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	17.25 ± 0.116	14.60 ± 0.095	27.35 ± 0.161	17.07 ± 0.102
110	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	67.16 ± 0.477	48.10 ± 0.303	59.65 ± 0.388	37.30 ± 0.272
111	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	49.47 ± 0.322	33.47 ± 0.244	40.91 ± 0.176	28.07 ± 0.202
112	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	99.31 ± 0.457	57.98 ± 0.267	75.04 ± 0.488	51.42 ± 0.242
113	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	269.33 ± 1.023	244.93 ± 1.053	268.26 ± 0.939	235.10 ± 1.129
114	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	522.14 ± 3.759	498.04 ± 3.735	523.20 ± 2.145	504.64 ± 1.867
115	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	298.45 ± 1.910	300.42 ± 2.013	300.11 ± 1.831	299.10 ± 1.854
116	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	552.59 ± 3.481	550.42 ± 2.147	552.95 ± 1.935	549.51 ± 2.418
117	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	269.88 ± 1.565	245.24 ± 1.692	267.10 ± 1.950	264.89 ± 1.695
118	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	531.41 ± 2.551	496.03 ± 3.175	529.42 ± 1.959	494.34 ± 2.373
119	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	281.02 ± 2.051	282.91 ± 1.895	279.34 ± 2.011	281.17 ± 1.462
120	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	538.33 ± 2.315	519.18 ± 3.115	534.98 ± 2.889	519.74 ± 3.534
121	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	151.86 ± 1.124	118.19 ± 0.496	187.49 ± 1.294	120.25 ± 0.445
122	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	439.71 ± 2.902	248.43 ± 1.739	364.90 ± 1.496	244.65 ± 1.199
123	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	286.80 ± 1.491	131.08 ± 0.773	267.10 ± 1.977	126.21 ± 0.480
124	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	581.82 ± 2.967	266.49 ± 1.412	582.92 ± 3.672	258.49 ± 1.628
125	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	184.37 ± 1.272	81.46 ± 0.375	221.66 ± 1.020	85.69 ± 0.531
126	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	465.22 ± 1.861	122.00 ± 0.732	523.08 ± 2.406	144.26 ± 1.010
127	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	279.64 ± 1.622	97.34 ± 0.399	292.24 ± 1.490	133.64 ± 0.508
128	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	578.78 ± 3.183	203.82 ± 1.121	570.52 ± 3.480	527.65 ± 3.324
129	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	20.20 ± 0.091	11.82 ± 0.050	17.55 ± 0.100	11.81 ± 0.054
130	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	92.31 ± 0.535	29.16 ± 0.125	61.75 ± 0.266	28.47 ± 0.122
131	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	45.03 ± 0.324	16.37 ± 0.087	35.17 ± 0.246	16.42 ± 0.085
132	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	308.82 ± 1.637	383.63 ± 1.650	309.69 ± 2.323	385.21 ± 1.810
133	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	24.71 ± 0.178	9.65 ± 0.065	23.15 ± 0.132	12.05 ± 0.059
134	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	83.18 ± 0.574	18.03 ± 0.070	53.14 ± 0.314	18.95 ± 0.074
135	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	42.02 ± 0.155	14.46 ± 0.074	37.57 ± 0.195	13.02 ± 0.079
136	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	283.51 ± 1.474	385.61 ± 1.851	333.53 ± 1.734	433.20 ± 1.646
137	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	11.00 ± 0.043	10.22 ± 0.045	11.07 ± 0.078	10.57 ± 0.071
138	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	22.88 ± 0.142	20.36 ± 0.122	23.16 ± 0.111	19.98 ± 0.120
139	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	12.77 ± 0.092	10.55 ± 0.057	12.38 ± 0.088	10.27 ± 0.071
140	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	44.66 ± 0.255	24.81 ± 0.127	32.50 ± 0.123	23.46 ± 0.127
141	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	13.01 ± 0.062	11.76 ± 0.082	7.16 ± 0.047	5.68 ± 0.043
142	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	15.22 ± 0.062	11.95 ± 0.051	10.32 ± 0.043	8.57 ± 0.032
143	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	11.64 ± 0.076	8.11 ± 0.039	9.53 ± 0.055	7.41 ± 0.039
144	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	52.56 ± 0.336	22.69 ± 0.111	40.69 ± 0.285	22.77 ± 0.132
145	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	151.09 ± 0.725	113.78 ± 0.853	151.94 ± 1.094	117.66 ± 0.777
146	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	449.65 ± 3.372	392.70 ± 2.749	448.21 ± 3.182	391.01 ± 1.877
147	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	234.84 ± 1.362	256.25 ± 1.179	239.78 ± 1.031	257.12 ± 0.977
148	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	548.93 ± 2.909	551.13 ± 2.480	547.69 ± 4.053	546.80 ± 3.828
149	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	153.77 ± 0.876	87.49 ± 0.560	177.94 ± 0.694	223.51 ± 1.118
150	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	416.75 ± 1.875	379.10 ± 2.464	445.24 ± 1.603	395.40 ± 1.661

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Table A.5: – continued from previous page

Instance ^a { $ \mathcal{N} $, $ \mathcal{N}^d $, \hat{T} , N , λ_i , γ , α_i , β_i }	Average cost per time unit and 95% confidence interval of heuristic n			
	1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R
151 {100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	239.37 ± 1.029	264.07 ± 1.373	242.83 ± 1.287	261.04 ± 1.671
152 {180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	537.44 ± 3.762	538.45 ± 3.985	548.50 ± 3.181	555.33 ± 3.388
153 {100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	37.66 ± 0.233	26.86 ± 0.094	34.53 ± 0.245	27.09 ± 0.157
154 {180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	156.92 ± 0.879	68.01 ± 0.408	94.83 ± 0.417	65.59 ± 0.485
155 {100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	106.50 ± 0.394	33.09 ± 0.185	63.22 ± 0.228	32.27 ± 0.142
156 {180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	419.00 ± 2.640	80.77 ± 0.541	416.37 ± 2.831	76.61 ± 0.444
157 {100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	30.75 ± 0.175	15.56 ± 0.110	26.12 ± 0.193	15.92 ± 0.105
158 {180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	165.17 ± 1.173	31.67 ± 0.139	220.34 ± 0.881	35.22 ± 0.250
159 {100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	92.57 ± 0.481	21.49 ± 0.088	63.92 ± 0.371	24.40 ± 0.142
160 {180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	385.20 ± 2.735	62.74 ± 0.452	427.12 ± 1.623	181.13 ± 0.869
161 {100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	36.32 ± 0.243	21.86 ± 0.081	30.99 ± 0.121	21.08 ± 0.120
162 {180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	150.99 ± 1.072	51.11 ± 0.383	101.03 ± 0.465	49.03 ± 0.343
163 {100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	88.41 ± 0.619	42.18 ± 0.257	77.18 ± 0.540	39.00 ± 0.269
164 {180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	348.40 ± 2.021	445.05 ± 2.359	354.61 ± 2.305	439.15 ± 1.757
165 {100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	51.41 ± 0.350	25.20 ± 0.141	42.85 ± 0.274	22.03 ± 0.117
166 {180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	149.13 ± 1.029	46.58 ± 0.224	111.10 ± 0.589	43.02 ± 0.168
167 {100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	73.05 ± 0.343	33.23 ± 0.126	74.88 ± 0.329	128.72 ± 0.901
168 {180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	337.23 ± 2.293	423.53 ± 2.160	376.06 ± 2.745	442.40 ± 2.300
169 {100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	15.87 ± 0.105	14.97 ± 0.066	17.40 ± 0.099	14.97 ± 0.079
170 {180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	34.87 ± 0.206	30.34 ± 0.134	36.92 ± 0.244	30.27 ± 0.106
171 {100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	24.70 ± 0.116	21.11 ± 0.095	24.53 ± 0.093	19.86 ± 0.085
172 {180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	80.67 ± 0.557	52.65 ± 0.390	64.49 ± 0.252	48.08 ± 0.250
173 {100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	21.86 ± 0.114	20.64 ± 0.144	12.79 ± 0.086	10.17 ± 0.045
174 {180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	41.95 ± 0.298	33.43 ± 0.177	31.88 ± 0.217	24.62 ± 0.158
175 {100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	27.59 ± 0.130	21.40 ± 0.075	22.32 ± 0.087	17.50 ± 0.077
176 {180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	135.21 ± 0.879	80.47 ± 0.604	88.64 ± 0.612	55.40 ± 0.404
177 {100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	179.82 ± 0.899	179.68 ± 0.988	178.69 ± 1.126	180.51 ± 1.119
178 {180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	488.64 ± 1.906	448.66 ± 1.840	490.65 ± 2.895	453.33 ± 3.309
179 {100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	267.43 ± 1.310	300.67 ± 1.293	268.17 ± 0.965	299.96 ± 1.470
180 {180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	576.40 ± 3.343	592.29 ± 2.606	578.44 ± 3.991	595.85 ± 4.231
181 {100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	168.60 ± 1.096	165.55 ± 0.927	209.57 ± 1.425	222.50 ± 1.268
182 {180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	483.87 ± 3.581	429.75 ± 1.934	488.46 ± 3.077	444.04 ± 3.019
183 {100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	250.05 ± 1.100	281.29 ± 1.941	248.61 ± 1.467	281.32 ± 0.985
184 {180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	581.48 ± 2.733	591.10 ± 3.192	585.66 ± 2.694	591.89 ± 4.380
185 {100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	73.13 ± 0.293	48.76 ± 0.254	61.56 ± 0.369	45.67 ± 0.320
186 {180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	224.06 ± 1.546	102.45 ± 0.625	142.50 ± 0.513	98.93 ± 0.584
187 {100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	163.50 ± 0.736	58.51 ± 0.298	112.02 ± 0.683	57.44 ± 0.373
188 {180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	496.37 ± 2.184	141.02 ± 0.973	498.50 ± 3.589	135.16 ± 0.635
189 {100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	66.03 ± 0.304	36.65 ± 0.187	51.67 ± 0.382	32.59 ± 0.169
190 {180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	199.11 ± 0.916	75.64 ± 0.325	115.90 ± 0.626	71.08 ± 0.405
191 {100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	138.00 ± 0.938	48.95 ± 0.289	97.79 ± 0.685	46.38 ± 0.306
192 {180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	484.24 ± 3.099	136.79 ± 0.711	496.79 ± 3.527	139.75 ± 0.936
193 {100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	108.73 ± 0.696	52.32 ± 0.340	88.37 ± 0.530	50.68 ± 0.213
194 {180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	311.27 ± 1.681	87.32 ± 0.629	223.31 ± 1.474	86.17 ± 0.310
195 {100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	175.49 ± 1.035	60.17 ± 0.325	162.27 ± 0.876	62.83 ± 0.352
196 {180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	982.71 ± 3.734	1394.87 ± 7.811	956.18 ± 4.972	1418.34 ± 6.241

Continued on next page

Table A.5: – continued from previous page

Instance ^a { $ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i$ }	Average cost per time unit and 95% confidence interval of heuristic n			
	1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R
197 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	71.50 ± 0.379	21.97 ± 0.088	80.73 ± 0.460	33.59 ± 0.144
198 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	326.23 ± 2.414	46.89 ± 0.249	264.38 ± 1.692	42.39 ± 0.309
199 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	133.05 ± 0.772	30.92 ± 0.127	101.22 ± 0.597	32.14 ± 0.193
200 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	1066.27 ± 5.438	1469.92 ± 9.848	1045.37 ± 3.763	1597.44 ± 7.827
201 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	45.03 ± 0.288	42.11 ± 0.240	49.19 ± 0.285	42.56 ± 0.277
202 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	83.16 ± 0.549	77.50 ± 0.403	85.45 ± 0.521	73.14 ± 0.285
203 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	45.88 ± 0.193	34.12 ± 0.154	43.68 ± 0.266	33.66 ± 0.219
204 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	86.07 ± 0.491	56.48 ± 0.316	80.13 ± 0.465	55.34 ± 0.271
205 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	23.50 ± 0.169	16.01 ± 0.114	20.89 ± 0.075	15.53 ± 0.113
206 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	31.14 ± 0.193	21.26 ± 0.074	26.81 ± 0.174	18.24 ± 0.097
207 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	33.76 ± 0.132	19.13 ± 0.082	28.68 ± 0.212	19.71 ± 0.095
208 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	84.92 ± 0.552	36.62 ± 0.146	71.14 ± 0.320	41.64 ± 0.267
209 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	615.20 ± 2.153	547.73 ± 2.848	632.00 ± 4.045	584.82 ± 2.456
210 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	1702.15 ± 12.085	1448.66 ± 8.837	1703.45 ± 8.006	1449.99 ± 7.250
211 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	929.34 ± 4.833	1020.59 ± 6.736	932.77 ± 5.876	1020.79 ± 5.104
212 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	2097.73 ± 10.279	2114.64 ± 13.745	2104.82 ± 7.788	2109.96 ± 11.394
213 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	661.14 ± 4.099	535.10 ± 2.194	654.09 ± 3.663	765.63 ± 3.216
214 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	1708.65 ± 9.739	1476.67 ± 9.303	1748.75 ± 11.017	1465.31 ± 7.913
215 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	833.57 ± 4.918	930.42 ± 3.908	954.12 ± 6.679	1092.90 ± 4.699
216 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	2117.18 ± 15.667	2167.14 ± 9.535	2123.90 ± 14.230	2150.04 ± 11.180
217 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	144.36 ± 0.606	105.53 ± 0.454	184.84 ± 0.906	106.55 ± 0.746
218 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	451.34 ± 2.708	196.80 ± 0.984	369.72 ± 2.699	195.87 ± 1.469
219 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	411.43 ± 1.934	125.08 ± 0.500	305.72 ± 1.376	130.30 ± 0.782
220 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	1597.58 ± 7.349	256.22 ± 1.614	1629.44 ± 7.658	245.04 ± 1.103
221 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	89.73 ± 0.314	42.37 ± 0.208	170.39 ± 0.818	51.20 ± 0.266
222 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	482.73 ± 3.476	74.67 ± 0.560	818.75 ± 4.094	92.38 ± 0.508
223 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	355.25 ± 2.060	58.65 ± 0.346	350.53 ± 2.138	111.73 ± 0.704
224 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.1 · α_i }	1455.02 ± 9.312	166.50 ± 1.099	1724.33 ± 6.897	1637.71 ± 11.464
225 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	99.73 ± 0.718	53.45 ± 0.337	78.55 ± 0.346	51.17 ± 0.348
226 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	431.09 ± 1.811	116.14 ± 0.859	325.17 ± 1.853	112.23 ± 0.438
227 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	193.18 ± 0.927	72.83 ± 0.291	162.61 ± 0.748	78.36 ± 0.525
228 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	1083.32 ± 8.125	1389.21 ± 6.390	1069.65 ± 4.279	1371.70 ± 9.328
229 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	72.23 ± 0.267	29.49 ± 0.127	81.25 ± 0.406	31.40 ± 0.185
230 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	397.03 ± 2.541	76.94 ± 0.346	342.53 ± 2.089	70.92 ± 0.454
231 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	177.39 ± 0.958	55.91 ± 0.285	163.80 ± 0.966	52.29 ± 0.308
232 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	1109.51 ± 5.326	1541.72 ± 6.938	1102.16 ± 7.274	1492.16 ± 9.251
233 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	55.59 ± 0.345	53.09 ± 0.271	51.88 ± 0.389	45.77 ± 0.165
234 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	97.42 ± 0.682	86.01 ± 0.456	97.33 ± 0.613	87.97 ± 0.449
235 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	78.99 ± 0.371	58.30 ± 0.257	72.20 ± 0.368	55.92 ± 0.207
236 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	127.32 ± 0.611	89.42 ± 0.617	116.93 ± 0.491	82.67 ± 0.546
237 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	32.58 ± 0.130	27.52 ± 0.190	28.65 ± 0.149	18.85 ± 0.104
238 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	102.82 ± 0.442	74.82 ± 0.554	72.61 ± 0.378	48.95 ± 0.367
239 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	47.95 ± 0.292	34.54 ± 0.197	41.56 ± 0.208	25.80 ± 0.144
240 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.1 · α_i }	134.78 ± 0.795	71.27 ± 0.271	109.19 ± 0.601	65.83 ± 0.270
241 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	645.34 ± 2.969	630.75 ± 3.469	664.09 ± 3.387	644.76 ± 3.224
242 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	1830.18 ± 8.053	1602.94 ± 7.694	1819.18 ± 9.096	1584.92 ± 7.766

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Table A.5: – continued from previous page

Instance ^a { $ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i$ }	Average cost per time unit and 95% confidence interval of heuristic n			
	1 SDSR	2 SDSR-R	3 SDDR	4 SDDR-R
243 {100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	1012.06 ± 7.489	1140.24 ± 8.552	1006.10 ± 6.640	1142.09 ± 4.568
244 {180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	2133.81 ± 15.790	2071.99 ± 8.910	2126.74 ± 9.145	2069.60 ± 10.555
245 {100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	603.07 ± 2.533	449.18 ± 2.785	598.47 ± 2.214	456.07 ± 1.916
246 {180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	1710.02 ± 8.721	1531.01 ± 8.727	1707.55 ± 7.342	1504.59 ± 9.930
247 {100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	960.21 ± 5.281	1062.78 ± 6.377	961.02 ± 5.190	1078.47 ± 5.932
248 {180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	2048.46 ± 11.471	2131.39 ± 10.444	2059.13 ± 14.826	2130.37 ± 11.078
249 {100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	163.69 ± 0.769	115.25 ± 0.703	215.61 ± 1.488	121.79 ± 0.743
250 {180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	506.06 ± 2.378	265.11 ± 1.935	405.98 ± 3.045	259.64 ± 1.428
251 {100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	407.41 ± 1.630	124.86 ± 0.737	354.79 ± 1.632	121.10 ± 0.799
252 {180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	1643.96 ± 5.754	343.81 ± 1.341	1655.72 ± 10.431	312.59 ± 2.282
253 {100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	95.06 ± 0.352	59.37 ± 0.338	184.65 ± 1.016	60.92 ± 0.366
254 {180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	677.72 ± 2.779	143.13 ± 0.615	964.93 ± 6.658	185.57 ± 0.724
255 {100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	353.74 ± 1.415	80.28 ± 0.586	327.48 ± 1.572	90.36 ± 0.651
256 {180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.1 · α_i }	1627.15 ± 9.600	250.96 ± 1.355	1923.82 ± 14.044	1600.92 ± 7.524

^a Here, $\alpha_i = 50$ means $U[50; 100]$ and $\alpha_i = 500$ means $U[100; 500]$.

Table A.6: Average cost per time unit and 95% confidence interval for each instance of large asymmetric test bed: heuristic 5-8

Instance ^a { $ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i$ }	Average cost per time unit and 95% confidence interval of heuristic n			
	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
1 {100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	21.37 ± 0.120	10.91 ± 0.073	17.14 ± 0.113	11.01 ± 0.075
2 {180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	53.51 ± 0.321	20.21 ± 0.103	42.14 ± 0.257	18.80 ± 0.137
3 {100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	29.75 ± 0.143	13.65 ± 0.086	28.97 ± 0.211	12.94 ± 0.050
4 {180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	60.44 ± 0.266	28.48 ± 0.145	60.05 ± 0.252	27.03 ± 0.165
5 {100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	14.83 ± 0.110	5.66 ± 0.042	12.38 ± 0.051	5.55 ± 0.032
6 {180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	42.93 ± 0.189	8.96 ± 0.058	27.77 ± 0.139	9.08 ± 0.064
7 {100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	25.20 ± 0.096	10.29 ± 0.038	23.81 ± 0.141	13.26 ± 0.072
8 {180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	50.69 ± 0.289	15.04 ± 0.092	50.50 ± 0.258	13.86 ± 0.086
9 {100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	10.95 ± 0.072	9.99 ± 0.054	10.67 ± 0.078	9.72 ± 0.043
10 {180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	22.44 ± 0.094	20.36 ± 0.102	22.92 ± 0.133	20.15 ± 0.077
11 {100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	11.76 ± 0.059	9.36 ± 0.067	11.62 ± 0.071	8.80 ± 0.040
12 {180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	30.22 ± 0.148	18.02 ± 0.074	26.36 ± 0.153	17.18 ± 0.091
13 {100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	6.67 ± 0.027	4.98 ± 0.019	5.44 ± 0.036	4.13 ± 0.015
14 {180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	16.22 ± 0.071	11.50 ± 0.056	12.19 ± 0.091	8.09 ± 0.042
15 {100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	14.61 ± 0.079	7.68 ± 0.040	11.56 ± 0.062	6.07 ± 0.043
16 {180, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.05 · α_i }	29.35 ± 0.191	14.90 ± 0.088	22.31 ± 0.143	11.27 ± 0.068
17 {100, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	59.51 ± 0.428	34.54 ± 0.162	58.87 ± 0.300	34.75 ± 0.215
18 {180, (0.4 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	105.93 ± 0.678	72.52 ± 0.297	104.84 ± 0.629	70.56 ± 0.416
19 {100, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	57.56 ± 0.201	44.49 ± 0.191	57.78 ± 0.364	42.79 ± 0.180
20 {180, (0.6 · $ \mathcal{N}^d $) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	106.31 ± 0.521	87.50 ± 0.324	105.22 ± 0.400	87.96 ± 0.484
21 {100, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	50.05 ± 0.210	18.33 ± 0.128	49.82 ± 0.264	18.41 ± 0.074
22 {180, (0.4 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	90.55 ± 0.498	40.80 ± 0.204	90.48 ± 0.326	46.12 ± 0.295
23 {100, (0.6 · $ \mathcal{N}^d $) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	51.33 ± 0.298	30.30 ± 0.200	51.53 ± 0.227	29.51 ± 0.148

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Table A.6: – continued from previous page

Instance ^a { $ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i$ }		Average cost per time unit and 95% confidence interval of heuristic n			
		5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
24	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	87.06 ± 0.522	58.13 ± 0.424	87.98 ± 0.563	65.43 ± 0.262
25	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	40.58 ± 0.158	31.25 ± 0.213	38.27 ± 0.188	30.42 ± 0.149
26	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	111.72 ± 0.749	55.00 ± 0.324	81.37 ± 0.399	54.61 ± 0.251
27	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	69.83 ± 0.405	29.69 ± 0.125	61.19 ± 0.233	29.95 ± 0.144
28	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	130.19 ± 0.820	53.01 ± 0.228	127.49 ± 0.714	51.76 ± 0.362
29	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	24.31 ± 0.168	11.15 ± 0.046	21.06 ± 0.154	11.03 ± 0.043
30	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	101.82 ± 0.509	24.38 ± 0.141	56.48 ± 0.254	25.08 ± 0.095
31	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	62.77 ± 0.370	17.51 ± 0.077	60.12 ± 0.397	20.29 ± 0.081
32	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.05 · α_i }	113.03 ± 0.441	28.10 ± 0.141	111.42 ± 0.501	29.31 ± 0.211
33	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	40.73 ± 0.289	18.88 ± 0.123	32.12 ± 0.202	19.28 ± 0.085
34	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	101.01 ± 0.455	43.44 ± 0.213	78.42 ± 0.290	40.39 ± 0.166
35	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	56.22 ± 0.360	27.10 ± 0.098	52.48 ± 0.210	25.62 ± 0.097
36	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	112.90 ± 0.440	60.57 ± 0.273	113.26 ± 0.770	56.51 ± 0.328
37	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	29.77 ± 0.167	15.22 ± 0.059	25.28 ± 0.121	15.17 ± 0.114
38	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	94.97 ± 0.342	38.29 ± 0.172	77.66 ± 0.318	34.80 ± 0.177
39	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	53.61 ± 0.214	27.13 ± 0.095	46.44 ± 0.348	25.27 ± 0.154
40	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	103.95 ± 0.468	50.91 ± 0.356	103.32 ± 0.362	49.51 ± 0.208
41	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	14.65 ± 0.073	14.10 ± 0.080	16.41 ± 0.085	13.97 ± 0.059
42	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	36.84 ± 0.133	33.47 ± 0.244	40.87 ± 0.155	34.14 ± 0.191
43	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	22.78 ± 0.121	18.41 ± 0.105	22.82 ± 0.082	18.15 ± 0.114
44	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	82.32 ± 0.486	51.93 ± 0.203	61.22 ± 0.294	41.80 ± 0.226
45	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	17.45 ± 0.112	15.46 ± 0.104	12.26 ± 0.075	10.75 ± 0.080
46	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	43.50 ± 0.261	35.85 ± 0.265	33.48 ± 0.161	26.43 ± 0.190
47	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	30.44 ± 0.213	21.52 ± 0.105	24.24 ± 0.085	17.76 ± 0.101
48	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.05 · α_i }	139.46 ± 1.004	87.98 ± 0.625	92.97 ± 0.493	46.97 ± 0.169
49	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	88.74 ± 0.426	55.79 ± 0.273	88.66 ± 0.665	54.18 ± 0.406
50	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	157.52 ± 0.551	121.05 ± 0.654	158.68 ± 0.793	119.53 ± 0.777
51	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	87.73 ± 0.316	71.14 ± 0.285	87.98 ± 0.414	71.30 ± 0.364
52	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	157.20 ± 0.692	137.64 ± 0.688	156.78 ± 0.721	137.50 ± 0.852
53	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	76.27 ± 0.313	40.07 ± 0.300	76.13 ± 0.548	39.20 ± 0.271
54	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	137.53 ± 0.523	87.59 ± 0.342	137.24 ± 0.714	86.38 ± 0.441
55	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	74.35 ± 0.335	53.92 ± 0.367	71.29 ± 0.499	60.94 ± 0.268
56	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	134.60 ± 0.808	106.64 ± 0.757	135.44 ± 0.772	105.50 ± 0.686
57	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	60.13 ± 0.295	42.01 ± 0.298	54.18 ± 0.347	40.74 ± 0.191
58	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	164.05 ± 0.771	90.76 ± 0.445	126.74 ± 0.798	89.25 ± 0.544
59	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	113.60 ± 0.829	52.26 ± 0.324	86.96 ± 0.600	50.49 ± 0.177
60	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	232.90 ± 1.700	105.34 ± 0.421	227.61 ± 0.797	99.49 ± 0.617
61	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	45.93 ± 0.197	27.13 ± 0.195	41.12 ± 0.300	26.74 ± 0.193
62	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	197.34 ± 0.967	77.74 ± 0.536	153.81 ± 0.892	69.99 ± 0.350
63	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	114.69 ± 0.837	44.69 ± 0.223	103.67 ± 0.560	43.75 ± 0.284
64	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.05 · α_i }	220.18 ± 1.233	102.13 ± 0.449	194.66 ± 0.934	96.07 ± 0.375
65	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	70.28 ± 0.372	38.21 ± 0.191	63.67 ± 0.325	38.82 ± 0.163
66	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	166.80 ± 0.617	66.55 ± 0.319	132.93 ± 0.811	63.55 ± 0.369
67	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	89.70 ± 0.457	38.72 ± 0.174	82.20 ± 0.592	35.81 ± 0.251
68	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	202.98 ± 0.771	88.80 ± 0.471	206.01 ± 1.318	80.87 ± 0.307
69	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	48.95 ± 0.343	15.82 ± 0.071	47.61 ± 0.190	15.45 ± 0.063

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Table A.6: – continued from previous page

Instance ^a { $ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i$ }		Average cost per time unit and 95% confidence interval of heuristic n			
		5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
70	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	142.13 ± 0.853	19.26 ± 0.110	127.02 ± 0.749	22.03 ± 0.110
71	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	71.63 ± 0.380	12.46 ± 0.066	65.76 ± 0.270	12.27 ± 0.080
72	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	160.03 ± 0.864	30.29 ± 0.121	158.79 ± 0.746	35.91 ± 0.165
73	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	36.05 ± 0.227	32.36 ± 0.165	36.29 ± 0.261	31.73 ± 0.140
74	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	90.92 ± 0.482	78.46 ± 0.518	86.52 ± 0.545	78.95 ± 0.466
75	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	39.21 ± 0.286	32.23 ± 0.187	39.31 ± 0.279	31.48 ± 0.161
76	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	90.14 ± 0.658	52.91 ± 0.254	82.07 ± 0.476	52.80 ± 0.264
77	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	13.89 ± 0.049	9.66 ± 0.071	12.15 ± 0.060	7.28 ± 0.028
78	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	63.31 ± 0.418	35.30 ± 0.159	44.92 ± 0.243	23.92 ± 0.093
79	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	24.84 ± 0.114	11.68 ± 0.051	21.34 ± 0.126	11.44 ± 0.059
80	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.05 · α_i }	69.45 ± 0.438	21.52 ± 0.114	55.94 ± 0.308	19.98 ± 0.122
81	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	207.90 ± 1.143	122.11 ± 0.488	209.34 ± 1.298	119.28 ± 0.513
82	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	389.57 ± 1.909	252.50 ± 1.515	390.85 ± 1.954	250.66 ± 1.454
83	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	217.64 ± 1.480	163.10 ± 1.158	216.45 ± 1.493	163.68 ± 0.737
84	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	377.71 ± 2.833	296.93 ± 2.168	378.28 ± 1.929	294.14 ± 2.147
85	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	187.02 ± 1.029	64.70 ± 0.278	185.75 ± 1.077	81.20 ± 0.487
86	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	299.48 ± 1.138	113.18 ± 0.804	309.75 ± 1.951	136.45 ± 0.955
87	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	174.48 ± 0.837	91.40 ± 0.521	174.19 ± 1.202	93.42 ± 0.448
88	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	306.38 ± 2.083	178.69 ± 1.322	310.52 ± 1.118	180.66 ± 1.102
89	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	135.45 ± 0.610	106.40 ± 0.458	142.50 ± 0.955	107.35 ± 0.526
90	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	356.19 ± 1.354	196.63 ± 0.728	300.87 ± 1.986	195.20 ± 0.800
91	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	214.89 ± 0.988	80.60 ± 0.282	205.78 ± 1.296	85.79 ± 0.635
92	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	400.12 ± 1.480	143.84 ± 0.604	401.75 ± 1.728	142.47 ± 0.969
93	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	162.90 ± 0.880	44.50 ± 0.276	182.62 ± 0.822	59.45 ± 0.262
94	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	312.51 ± 1.938	49.72 ± 0.293	361.44 ± 1.735	66.03 ± 0.258
95	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	167.05 ± 0.885	26.63 ± 0.154	137.39 ± 1.017	24.66 ± 0.101
96	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 500, 0.05 · α_i }	352.36 ± 2.255	47.79 ± 0.306	348.44 ± 2.125	50.40 ± 0.192
97	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	91.79 ± 0.542	51.32 ± 0.195	78.00 ± 0.413	49.03 ± 0.353
98	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	239.32 ± 1.005	97.34 ± 0.399	210.89 ± 1.434	93.79 ± 0.328
99	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	132.27 ± 0.860	58.68 ± 0.381	122.65 ± 0.429	54.79 ± 0.389
100	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	252.81 ± 1.567	116.89 ± 0.818	253.50 ± 1.344	109.66 ± 0.570
101	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	75.76 ± 0.568	27.12 ± 0.119	81.12 ± 0.487	27.82 ± 0.100
102	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	195.87 ± 0.881	46.41 ± 0.283	183.21 ± 1.008	46.71 ± 0.308
103	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	85.50 ± 0.445	26.63 ± 0.141	81.85 ± 0.598	25.48 ± 0.171
104	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	198.53 ± 1.290	62.77 ± 0.395	198.60 ± 1.072	59.69 ± 0.430
105	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	37.57 ± 0.244	34.46 ± 0.248	41.51 ± 0.241	36.00 ± 0.130
106	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	100.71 ± 0.735	91.43 ± 0.448	104.28 ± 0.553	89.05 ± 0.606
107	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	40.15 ± 0.165	34.95 ± 0.196	44.48 ± 0.298	34.70 ± 0.163
108	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	118.89 ± 0.773	70.86 ± 0.432	98.69 ± 0.395	64.37 ± 0.380
109	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	16.43 ± 0.066	13.62 ± 0.060	26.05 ± 0.151	15.64 ± 0.100
110	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	68.35 ± 0.273	46.14 ± 0.254	57.38 ± 0.252	34.23 ± 0.144
111	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	53.00 ± 0.276	29.98 ± 0.147	41.53 ± 0.228	23.08 ± 0.168
112	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 500, 0.05 · α_i }	98.52 ± 0.404	49.40 ± 0.296	75.52 ± 0.446	41.19 ± 0.185
113	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	237.62 ± 1.735	145.37 ± 0.552	234.70 ± 1.713	142.36 ± 1.068
114	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	425.42 ± 2.127	288.16 ± 1.844	424.15 ± 2.333	281.10 ± 1.911
115	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	235.94 ± 1.133	175.92 ± 1.091	234.10 ± 1.171	174.04 ± 1.044

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Table A.6: – continued from previous page

Instance ^a { $ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i$ }	Average cost per time unit and 95% confidence interval of heuristic n			
	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
116 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	409.78 ± 1.762	336.88 ± 1.718	415.24 ± 1.993	338.69 ± 2.134
117 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	202.78 ± 0.953	78.42 ± 0.282	204.35 ± 1.512	119.48 ± 0.514
118 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	358.67 ± 1.255	161.93 ± 0.761	363.60 ± 2.654	162.21 ± 1.054
119 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	187.98 ± 1.297	99.42 ± 0.467	186.55 ± 0.858	98.97 ± 0.435
120 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	336.20 ± 1.446	220.78 ± 0.949	333.29 ± 1.866	223.21 ± 0.826
121 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	148.69 ± 0.907	115.63 ± 0.740	181.88 ± 1.055	116.84 ± 0.432
122 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	408.03 ± 2.367	230.85 ± 1.339	364.89 ± 1.824	232.35 ± 1.417
123 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	264.27 ± 1.031	110.21 ± 0.727	224.33 ± 1.301	110.05 ± 0.418
124 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	513.91 ± 3.803	202.57 ± 1.458	510.83 ± 3.780	202.04 ± 1.394
125 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	178.60 ± 0.643	73.58 ± 0.390	181.42 ± 0.907	69.62 ± 0.459
126 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	386.81 ± 2.282	98.18 ± 0.668	422.41 ± 2.366	107.71 ± 0.539
127 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	252.82 ± 1.466	73.44 ± 0.264	247.44 ± 1.683	85.86 ± 0.352
128 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 500, 0.05 · α_i }	460.59 ± 3.178	131.43 ± 0.631	425.19 ± 1.828	148.27 ± 1.023
129 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	19.94 ± 0.136	10.66 ± 0.078	17.06 ± 0.128	10.59 ± 0.060
130 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	77.22 ± 0.363	23.49 ± 0.139	53.96 ± 0.367	21.90 ± 0.107
131 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	39.15 ± 0.141	11.66 ± 0.063	32.36 ± 0.197	11.34 ± 0.051
132 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	104.69 ± 0.660	31.97 ± 0.125	105.38 ± 0.400	30.14 ± 0.211
133 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	24.51 ± 0.142	7.48 ± 0.026	22.13 ± 0.108	7.76 ± 0.049
134 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	63.39 ± 0.431	11.67 ± 0.082	40.37 ± 0.206	11.34 ± 0.050
135 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	32.95 ± 0.247	7.64 ± 0.054	30.80 ± 0.157	7.17 ± 0.051
136 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	81.86 ± 0.450	16.94 ± 0.122	78.91 ± 0.410	20.05 ± 0.098
137 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	10.62 ± 0.045	10.30 ± 0.040	11.32 ± 0.067	10.30 ± 0.061
138 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	22.56 ± 0.086	20.15 ± 0.141	23.48 ± 0.110	19.83 ± 0.091
139 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	12.25 ± 0.073	10.00 ± 0.068	11.93 ± 0.084	9.52 ± 0.063
140 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	44.42 ± 0.262	22.25 ± 0.091	32.67 ± 0.170	18.81 ± 0.105
141 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	13.12 ± 0.070	11.11 ± 0.049	7.85 ± 0.042	4.89 ± 0.024
142 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	15.04 ± 0.066	11.06 ± 0.040	10.56 ± 0.067	7.48 ± 0.030
143 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	11.57 ± 0.065	6.98 ± 0.045	9.34 ± 0.033	5.94 ± 0.029
144 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 50, 0.1 · α_i }	50.51 ± 0.379	19.46 ± 0.095	33.67 ± 0.219	14.89 ± 0.074
145 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	81.08 ± 0.543	38.85 ± 0.218	81.35 ± 0.537	37.55 ± 0.161
146 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	156.26 ± 0.859	83.27 ± 0.300	156.07 ± 0.780	83.14 ± 0.582
147 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	88.66 ± 0.372	55.10 ± 0.198	87.79 ± 0.518	53.99 ± 0.378
148 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	168.32 ± 0.606	120.14 ± 0.577	171.38 ± 0.703	122.54 ± 0.711
149 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	66.36 ± 0.292	19.60 ± 0.092	69.13 ± 0.346	41.82 ± 0.159
150 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	117.44 ± 0.787	45.48 ± 0.318	118.13 ± 0.721	60.58 ± 0.394
151 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	72.23 ± 0.347	37.89 ± 0.250	73.49 ± 0.323	36.68 ± 0.136
152 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	135.93 ± 0.612	83.15 ± 0.491	144.45 ± 1.040	95.60 ± 0.335
153 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	36.79 ± 0.199	25.31 ± 0.177	33.71 ± 0.152	25.54 ± 0.161
154 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	128.29 ± 0.539	62.65 ± 0.457	93.92 ± 0.573	61.32 ± 0.380
155 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	89.06 ± 0.338	27.37 ± 0.142	60.67 ± 0.431	25.74 ± 0.188
156 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	215.12 ± 1.183	54.76 ± 0.361	212.11 ± 0.870	53.46 ± 0.262
157 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	29.66 ± 0.151	13.50 ± 0.063	25.01 ± 0.163	13.39 ± 0.094
158 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	115.63 ± 0.543	24.04 ± 0.168	77.59 ± 0.497	24.21 ± 0.155
159 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	75.52 ± 0.430	15.37 ± 0.069	50.21 ± 0.286	15.94 ± 0.078
160 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 1, 50, 0.1 · α_i }	177.44 ± 1.295	33.27 ± 0.186	168.43 ± 0.977	37.66 ± 0.230
161 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	36.52 ± 0.172	20.24 ± 0.087	30.41 ± 0.140	19.30 ± 0.131

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Table A.6: – continued from previous page

Instance ^a { $ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i$ }	Average cost per time unit and 95% confidence interval of heuristic n			
	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
162 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	120.06 ± 0.852	44.43 ± 0.253	87.14 ± 0.619	41.26 ± 0.169
163 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	73.18 ± 0.315	30.71 ± 0.111	67.97 ± 0.483	29.69 ± 0.193
164 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	155.37 ± 1.072	68.83 ± 0.248	155.03 ± 0.853	65.61 ± 0.446
165 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	48.11 ± 0.221	23.03 ± 0.081	37.84 ± 0.174	18.05 ± 0.094
166 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	117.23 ± 0.832	36.25 ± 0.225	87.43 ± 0.437	33.84 ± 0.152
167 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	60.63 ± 0.358	23.66 ± 0.114	53.74 ± 0.306	22.93 ± 0.096
168 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	133.92 ± 0.536	56.91 ± 0.233	124.63 ± 0.511	58.88 ± 0.218
169 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	15.66 ± 0.113	14.59 ± 0.099	17.29 ± 0.085	15.02 ± 0.075
170 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	34.02 ± 0.245	29.42 ± 0.150	35.59 ± 0.128	29.73 ± 0.113
171 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	24.99 ± 0.130	19.87 ± 0.103	25.36 ± 0.150	19.77 ± 0.103
172 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	77.41 ± 0.356	47.50 ± 0.171	66.03 ± 0.489	41.99 ± 0.227
173 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	21.31 ± 0.134	20.54 ± 0.082	12.58 ± 0.054	9.72 ± 0.046
174 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	41.14 ± 0.284	31.66 ± 0.190	33.16 ± 0.159	22.62 ± 0.133
175 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	27.38 ± 0.162	20.24 ± 0.073	21.50 ± 0.075	16.25 ± 0.086
176 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 4, 50, 0.1 · α_i }	133.14 ± 0.546	77.00 ± 0.293	82.01 ± 0.525	44.59 ± 0.254
177 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	108.58 ± 0.391	62.95 ± 0.315	108.29 ± 0.455	61.81 ± 0.334
178 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	205.15 ± 1.272	131.33 ± 0.630	205.72 ± 1.029	131.33 ± 0.683
179 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	116.84 ± 0.806	81.85 ± 0.426	117.54 ± 0.705	82.75 ± 0.612
180 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	214.70 ± 1.524	168.18 ± 1.211	214.91 ± 0.903	164.83 ± 1.203
181 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	91.69 ± 0.578	42.80 ± 0.197	87.96 ± 0.413	53.75 ± 0.258
182 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	171.49 ± 1.166	93.23 ± 0.559	171.68 ± 1.082	95.59 ± 0.468
183 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	93.58 ± 0.646	57.38 ± 0.413	93.12 ± 0.466	57.39 ± 0.425
184 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	188.75 ± 0.698	133.62 ± 0.922	186.62 ± 0.858	134.95 ± 0.769
185 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	73.28 ± 0.381	46.72 ± 0.182	60.47 ± 0.375	43.39 ± 0.182
186 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	194.27 ± 0.797	92.11 ± 0.405	138.88 ± 0.750	88.78 ± 0.559
187 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	145.85 ± 0.613	50.47 ± 0.353	100.06 ± 0.640	49.50 ± 0.208
188 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	310.00 ± 1.829	110.80 ± 0.776	309.59 ± 1.331	104.87 ± 0.703
189 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	64.64 ± 0.297	33.91 ± 0.220	49.90 ± 0.339	29.27 ± 0.158
190 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	167.52 ± 0.653	63.95 ± 0.339	113.71 ± 0.796	60.09 ± 0.397
191 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	121.59 ± 0.535	40.36 ± 0.182	87.81 ± 0.606	39.41 ± 0.185
192 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.01; 0.05]$, 4, 50, 0.1 · α_i }	279.33 ± 1.899	97.75 ± 0.371	263.81 ± 0.950	93.38 ± 0.570
193 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	100.88 ± 0.545	43.79 ± 0.263	84.70 ± 0.584	44.10 ± 0.322
194 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	251.91 ± 1.209	69.54 ± 0.341	183.71 ± 1.066	66.36 ± 0.385
195 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	147.96 ± 0.681	35.67 ± 0.260	125.48 ± 0.803	35.95 ± 0.262
196 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	330.76 ± 1.323	86.96 ± 0.600	329.18 ± 1.448	79.80 ± 0.519
197 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	72.91 ± 0.423	14.81 ± 0.104	66.10 ± 0.251	19.87 ± 0.129
198 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	229.13 ± 0.917	20.06 ± 0.116	192.92 ± 0.907	19.80 ± 0.107
199 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	96.42 ± 0.376	12.31 ± 0.087	81.95 ± 0.303	11.41 ± 0.074
200 {180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	265.08 ± 0.981	29.93 ± 0.108	263.05 ± 1.499	32.58 ± 0.156
201 {100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	45.85 ± 0.238	42.98 ± 0.198	47.52 ± 0.171	42.86 ± 0.193
202 {180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	84.89 ± 0.467	74.00 ± 0.377	84.41 ± 0.346	71.96 ± 0.403
203 {100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	47.06 ± 0.344	32.33 ± 0.200	41.07 ± 0.259	31.32 ± 0.163
204 {180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	93.41 ± 0.430	45.41 ± 0.313	78.60 ± 0.283	44.29 ± 0.244
205 {100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	22.53 ± 0.104	14.75 ± 0.105	19.40 ± 0.130	12.75 ± 0.084
206 {180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	31.13 ± 0.190	15.65 ± 0.108	26.71 ± 0.166	13.24 ± 0.068
207 {100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor$, $U[0.001; 0.01]$, 1, 500, 0.1 · α_i }	31.59 ± 0.130	16.20 ± 0.081	28.70 ± 0.198	14.55 ± 0.084

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Table A.6: – continued from previous page

Instance ^a { $ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i$ }		Average cost per time unit and 95% confidence interval of heuristic n			
		5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
208	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 1, 500, 0.1 \cdot \alpha_i$ }	89.66 ± 0.457	26.05 ± 0.112	61.55 ± 0.326	23.10 ± 0.134
209	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	305.29 ± 1.771	146.14 ± 0.716	300.32 ± 2.132	136.53 ± 0.983
210	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	556.08 ± 3.559	283.24 ± 2.096	556.43 ± 3.728	280.65 ± 1.684
211	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	328.81 ± 1.480	191.70 ± 1.035	329.60 ± 1.384	192.04 ± 0.999
212	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	636.93 ± 2.229	449.71 ± 2.024	639.62 ± 3.390	457.45 ± 2.150
213	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	259.81 ± 1.273	69.76 ± 0.502	269.70 ± 1.672	94.08 ± 0.358
214	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	441.12 ± 2.470	141.91 ± 1.036	442.93 ± 3.012	139.77 ± 0.769
215	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	226.80 ± 1.474	82.93 ± 0.290	310.94 ± 1.399	239.57 ± 1.605
216	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	487.06 ± 3.263	266.51 ± 1.173	485.52 ± 2.670	259.71 ± 1.870
217	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	138.58 ± 0.582	100.26 ± 0.451	181.47 ± 0.871	101.95 ± 0.551
218	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	392.87 ± 2.082	174.10 ± 1.114	368.38 ± 1.510	176.62 ± 1.095
219	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	339.91 ± 2.039	105.05 ± 0.420	273.65 ± 1.861	107.32 ± 0.773
220	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	780.13 ± 3.511	167.60 ± 1.257	781.89 ± 4.770	162.35 ± 0.828
221	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	91.37 ± 0.530	32.86 ± 0.246	185.52 ± 1.150	38.03 ± 0.281
222	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	366.07 ± 1.977	44.62 ± 0.330	379.21 ± 2.199	58.29 ± 0.431
223	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	274.76 ± 1.511	35.05 ± 0.245	280.55 ± 1.459	49.04 ± 0.275
224	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 1, 500, 0.1 \cdot \alpha_i$ }	612.28 ± 4.286	67.05 ± 0.255	573.08 ± 2.006	118.74 ± 0.665
225	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	103.68 ± 0.746	46.90 ± 0.202	77.47 ± 0.449	45.68 ± 0.192
226	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	331.28 ± 1.193	89.50 ± 0.671	241.10 ± 1.664	86.50 ± 0.329
227	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	166.75 ± 0.850	51.61 ± 0.351	140.68 ± 0.619	50.65 ± 0.355
228	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	383.00 ± 1.340	109.65 ± 0.658	376.33 ± 1.656	104.47 ± 0.418
229	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	68.82 ± 0.255	22.30 ± 0.100	79.98 ± 0.544	24.35 ± 0.093
230	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	270.50 ± 2.029	46.33 ± 0.306	233.05 ± 0.979	46.41 ± 0.255
231	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	132.86 ± 0.917	29.37 ± 0.153	120.09 ± 0.757	29.83 ± 0.164
232	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	319.59 ± 1.342	62.30 ± 0.380	320.13 ± 2.209	60.56 ± 0.236
233	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	56.48 ± 0.220	49.00 ± 0.343	50.83 ± 0.315	45.20 ± 0.316
234	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	96.20 ± 0.616	83.65 ± 0.586	99.60 ± 0.428	82.80 ± 0.389
235	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	81.42 ± 0.415	55.21 ± 0.210	71.86 ± 0.474	52.79 ± 0.391
236	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	132.29 ± 0.833	74.91 ± 0.390	110.92 ± 0.510	76.61 ± 0.398
237	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	32.70 ± 0.128	26.50 ± 0.114	26.83 ± 0.164	17.54 ± 0.068
238	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	100.25 ± 0.461	70.00 ± 0.266	71.57 ± 0.508	39.98 ± 0.160
239	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	50.38 ± 0.373	30.36 ± 0.206	41.55 ± 0.307	21.90 ± 0.103
240	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.001; 0.01], 4, 500, 0.1 \cdot \alpha_i$ }	132.46 ± 0.636	58.53 ± 0.299	106.01 ± 0.541	46.58 ± 0.219
241	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	332.95 ± 1.299	169.25 ± 0.677	334.13 ± 2.072	166.11 ± 0.997
242	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	634.11 ± 4.502	356.07 ± 2.243	635.77 ± 3.815	354.49 ± 1.950
243	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	380.53 ± 1.712	243.73 ± 1.365	384.78 ± 2.693	233.59 ± 1.705
244	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	653.62 ± 4.902	461.59 ± 2.816	667.68 ± 4.340	468.83 ± 1.875
245	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	268.40 ± 1.369	79.24 ± 0.578	264.10 ± 1.637	78.02 ± 0.289
246	{180, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	476.00 ± 3.570	181.18 ± 0.670	474.61 ± 2.848	180.23 ± 0.901
247	{100, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	280.37 ± 1.234	135.30 ± 0.825	282.15 ± 1.044	130.04 ± 0.728
248	{180, (0.6 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{1}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	512.55 ± 2.358	296.59 ± 1.097	522.07 ± 2.036	304.54 ± 1.370
249	{100, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	163.06 ± 0.669	109.84 ± 0.428	209.20 ± 0.732	113.11 ± 0.599
250	{180, (0.4 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	461.47 ± 2.446	239.35 ± 0.838	391.27 ± 2.387	234.26 ± 1.663
251	{100, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	347.47 ± 2.502	98.89 ± 0.593	307.67 ± 1.938	102.09 ± 0.613
252	{180, (0.6 · \mathcal{N}^d) ² , [1 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	858.54 ± 6.010	231.93 ± 0.905	858.35 ± 3.176	217.88 ± 1.569
253	{100, (0.4 · \mathcal{N}^d) ² , [1.5 · $\sqrt{\frac{ \mathcal{N} }{N}}$], $\lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i$ }	96.14 ± 0.596	50.13 ± 0.376	181.33 ± 1.070	52.20 ± 0.313

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Table A.6: – continued from previous page

Instance ^a $\{ \mathcal{N} , \mathcal{N}^d , \hat{T}, N, \lambda_i, \gamma, \alpha_i, \beta_i\}$	Average cost per time unit and 95% confidence interval of heuristic n			
	5 DDSR	6 DDSR-R	7 DDDR	8 DDDR-R
254 $\{180, (0.4 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	530.43 ± 3.713	113.34 ± 0.453	630.46 ± 2.837	131.65 ± 0.922
255 $\{100, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	293.97 ± 1.999	56.59 ± 0.419	279.92 ± 1.176	60.93 ± 0.366
256 $\{180, (0.6 \cdot \mathcal{N}^d)^2, [1.5 \cdot \sqrt{\frac{ \mathcal{N} }{N}}], \lfloor \frac{2}{10} \cdot \mathcal{N}^d \rfloor, U[0.01; 0.05], 4, 500, 0.1 \cdot \alpha_i\}$	742.04 ± 3.636	141.06 ± 0.522	669.54 ± 2.410	172.06 ± 1.204