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MODELING AND SIMULATION FOR THE OPERATIVE SERVICE DELIVERY PLANNING IN THE CONTEXT OF PRODUCT-SERVICE SYSTEMS

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ABSTRACT

Accelerated with the developments in the context of Industry 4.0, a new trend has established itself in the manufacturing industry within the last two decades. Companies started to offer integrated solutions such as Product-Service Systems (PSS). While the provision of PSS enables benefits like business model innovation or strengthening competitiveness, the exploitation of these benefits depends heavily on the decisions in the operative service delivery planning. This, however, is a complex task due to the huge solution space. Analytical methods reach their limitations when trying to find the optimal solution. Though different optimization algorithms were elaborated for this problem, the evaluation of their solutions is overly simplified, and thus, their expressiveness for the uncertain and dynamic reality remains questionable. This paper addresses these issues by demonstrating the modeling of an adaptive simulation model that can be used to gain a realistic evaluation of operative service delivery plans in PSS.

1 INTRODUCTION

In light of globalization, intense competition, and declining profitability, manufacturing firms are reconsidering their product portfolios (Brissaud et al. 2022). At the same time, the emergence of Industry 4.0 and the rapid advancement of information and communication technologies enabled manufacturers to follow new ways to enhance their competitiveness. One strategy that has gained traction is the adoption of *Servitization*. Manufacturing firms started to add services to their physical products in order to create a higher customer value (Mahl et al. 2021). In literature, such combinations of services and products are called Product-Service Systems (PSS). PSS are integrated solutions that aim to fulfill customer needs. They are often offered in innovative business models, where the focus is not on the product itself, but on its benefits for the customer (Moro et al. 2022). Such business models also highlight the importance of digital technologies. Even when the technical product is in operation at the customer´s site, the provider must, ideally, track the status of the product via intelligent sensors in order the ensure its usability by delivering suitable services (Pirola et al. 2020).

With high efficiency during the use phase of PSS, providers can achieve economic and environmental benefits by offering such innovative business models (Kim et al. 2023). Nevertheless, this phase presents a significant challenge for PSS providers, particularly concerning the operative service delivery planning. Here, the task is to create plans by allocating resources to customers´ orders and scheduling their execution. Due to the huge solution space of this task, it can be formulated as an optimization problem (Dorka et al. 2014). Despite its inherent complexity, many dispatchers rely solely on their experiences, eschewing the use of decision support systems (Sala, Pirola et al. 2021). Approaches in the literature aim to automate decision-making by evaluating created plans with analytical models (see Subsection 2.3). However, reality is characterized by uncertainties and dynamic changes, which makes it difficult to rely solely on analytical models. Therefore, there is a need for evaluation tools that are capable of incorporating uncertainties in service delivery.

One approach to address this need is to conduct a simulation-based evaluation of the created plans, as simulations are capable of considering uncertainties in complex systems (Chica et al. 2017). Such an approach allows dispatchers and automated decision-makers (optimization algorithms) to test different scenarios and evaluate the quality of the plan under various conditions. Thus, the paper at hand seeks to answer the following research questions (RQ):

RQ 1: How can the service delivery be modeled and simulated to evaluate operative delivery plans?
  1.1: What agents are needed and what are their characteristics?
  1.2: How can different service processes be modeled and implemented?
  1.3.: How can the dispatching and scheduling be modeled and implemented?
RQ 2: How can the model be designed to be adaptive?

The remainder of this paper is structured as follows. Section 2 provides foundational information on PSS and their business models, as well as an introduction to the challenges in the operative service delivery planning. In Subsection 2.3, the need for a simulation-based evaluation tool for operative service delivery plans is highlighted. Section 3 describes the formalization of our model and design decisions. In Section 4, the implementation of the model and its key features are explained. Section 5 outlines the experiments conducted to evaluate the model. Finally, in Section 6, concluding remarks and an outlook for future research are given.

2 BACKGROUND AND FOUNDATIONS

2.1 Product-Service Systems

The phenomenon of Servitization (Kowalkowski et al. 2017) and the adoption of PSS in the manufacturing sector have been accelerated with the emergence of Industry 4.0. Technological innovations like the Internet of Things, cyber-physical systems, big data, artificial intelligence, and digital twins enabled manufacturing companies to offer new hybrid solutions in the sense of PSS (Kim et al. 2023). PSS can be defined as “a marketable set of products and services capable of jointly fulfilling a user´s need” (Goedkopp et al. 1999). Thus, the focus shifts from the product itself to the realization of a customer-centric value proposition. By offering PSS, companies target to achieve higher revenues, stronger customer relationships, and better environmental performance (Li et al. 2020).

Usually, PSS are provided in innovative business models. Depending on the proposed value and the way revenues are generated, PSS business models can be divided into three main categories: product-oriented, use-oriented, and result-oriented business models. In product-oriented business models, customers buy the product and agree on additional services, e.g., maintenance or recycling. In use-oriented business models, customers do not pay for the product itself but for its availability or usage of it. The ownership of the product remains at the provider, and he becomes responsible for achieving the agreed availability and paying a penalty if not. The responsibilities of the provider are increased in result-oriented business models. In these business models, the provider promises to deliver a particular result or outcome with the product (Reim et al. 2015). Compared to traditional business models, the characteristic feature of these innovative business models is that activities that were conducted by the customer before are now transferred to the providers' area of responsibility. In this way, customers can concentrate on their core competencies and profit from avoiding high investment risks in purchasing products. On the other hand, providers benefit from higher customer proximity, long-term customer relationships, and continuous revenues (Meier, Roy, Seliger 2010).

Although, the advantages of adopting PSS are obvious for the providers and customers, exploiting these advantages remains a complex challenge. This is because it is no longer sufficient for manufacturers to efficiently produce a high-quality product. Rather, being a PSS provider demands an efficient and satisfying delivery of the necessary services in order to realize the value proposition. This is particularly important when having customers with use-oriented business models. If the efficiency of the service delivery is low in this kind of business model, not only does the provider have to expect to pay penalties and have additional costs, but the trust and satisfaction of the customer will decrease which will lead to a negative impact on the relationship (Sala, Bertoni et al. 2021). Consequently, decisions that are made in the operative service delivery planning play a crucial role in the success of PSS business models (Alp et al. 2022).

2.2 Operative Service Delivery Planning in Product-Service Systems

Service planning in PSS can be differentiated into strategic and operative planning. Strategic planning involves making long-term decisions in order to build up the necessary quantity and quality of resources. The capacities determined here frame the decisions in the operative planning (Lagemann and Meier 2014). Operative planning is a short-term planning process, typically managed by a dispatcher (see Figure 1). His aim is to allocate the right resources to specific orders, schedule the delivery of services, and determine suitable routes for delivery (Dorka et al. 2015).

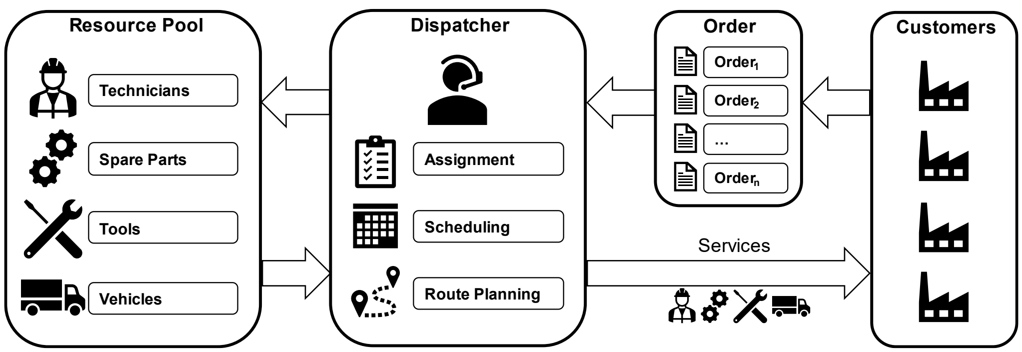

Figure 1: Operative Service Delivery Planning in Product-Service Systems (Alp et al. 2022)

Orders are generated by geographically dispersed customers, vary in duration and complexity of the requested processes, and must be completed within a specified time window. In the allocation of resources to the tasks, technicians who execute the tasks turn out to be the most critical resource in the pool. Their working time is limited. Overtime and overnights can be planned but lead to additional costs and are not preferred for reasons of employee satisfaction. Besides, technicians differ in their qualifications and competencies which affects their effectiveness and efficiency during service delivery. Inexperienced technicians with low qualifications can deliver simple standard processes but are not suitable for executing complex tasks whereas expert technicians are able to deliver all kinds of tasks (Sala, Pirola et al. 2021). Moreover, they can also assist the inexperienced technicians remotely by staying at the headquarter and using e.g., augmented, or virtual reality. In this way, their travel times can be minimized so that a higher effective working time is achieved (Aquino et al. 2023). Not all tasks may require spare parts and certain tasks may demand the use of specific tools. Depending on the urgency of the tasks, the dispatcher could choose to assign different vehicles e. g. cars or trains (Meier, Funke, Boßlau 2011).

Even though the operative service delivery planning in PSS has a large intersection with the classical field service planning like in (Lin et al. 2002) or the Vehicle Routing Problem with Time Windows (Kallehauge et al. 2005), there are also some peculiarities due to the innovative business models. In the context of PSS, orders and service processes can also be initiated by the provider himself. Due to the high level of customer proximity, the uncertainties regarding unexpected events such as machine failures are less. At the same time, the flexibility in fulfilling orders is higher. The fact that the value proposition in use-oriented business models, for instance, is the monthly availability of the technical asset enables the provider to decide how to realize this availability. He could decide to repair, or replace certain parts or even exchange the whole technical asset with another one (Meier, Völker et al. 2011). Moreover, the provider could also decide to integrate external partners like additional service providers to execute certain tasks. Besides, the business model characteristics not only increase the flexibility but also the requirements for the planning solution since penalties due to low availability and reduction of customer trust and satisfaction must be prevented (Meier, Uhlmann et al. 2010).

The main goal in operative service delivery planning is to create a plan that leads to minimal costs, maximal punctuality, and a leveled utilization of technicians. Reaching this goal is a highly complex task because the solution space of possible plans is enormously large (Meier, Funke, Boßlau 2011). To give an example, for the determination of the sequence of 30 tasks, there are $30! = 2{,}65 * 10^{32}$ possibilities. This number is further increased by the various flexibility option in the context of PSS business models. Accordingly, the main challenge in operative service planning is to find the optimal or at least a "good-enough" plan (Meier, Völker et al. 2011).

While it is evident that decision-making plays a crucial role in the service delivery phase (Sala et al. 2019), many decisions during the resource allocation and order scheduling are still made manually based on the experiences and knowledge of the dispatcher by e.g., using Excel spreadsheets (Sala, Pirola et al. 2021). This arises the need for advanced decision support tools that are capable of evaluating these decisions or even automating the task of allocation and scheduling (Vössing et al. 2018).

2.3 Related Work and Motivation

The issue of operative service delivery planning in PSS gained higher interest in recent years. The proposed approaches mainly focus on the automation of decision-making and optimizing delivery plans regarding different constraints. Ding et al. (2017) present a metaheuristic algorithm working on a mathematical problem formulation to optimize operative service plans toward environmental and economic sustainability. Dan et al. (2018) also start with a mathematical formulation of the problem and develop a Mixed-Integer Linear Programming algorithm for the optimization. Zhang et al. (2019) develop and compare three different metaheuristics for the optimization of order scheduling based on a mathematical formulation. Sala, Pirola et al. (2021) present an approach for optimizing the tardiness of service delivery using mathematical optimization in the software Cplex.

The analysis of existing approaches leads to the insight that these decision support systems are typically composed of two main components. The first component, the **plan generator component**, involves the automation of dispatchers´ work by running intelligent algorithms to generate new plans. The second component, the **plan evaluator component**, is responsible for evaluating the generated plans regarding their quality and optimality and sending feedback to the first component. By the iteration of both components, the optimization of the operative service delivery planning is realized.

In the existing approaches, the plan evaluator component used mathematical formulations of the problem to assess the given plans in a deterministic manner. However, in reality, the execution of plans is associated with many uncertainties. To have a more realistic evaluation of a plan, the evaluation method should be capable of considering stochastic elements especially, regarding the duration of service delivery. According to Chica et al. (2017) ,the best approach for dealing with uncertain complex systems is simulation modeling since it allows the representation of the real system in the desired level of detail. The execution of the plans can be evaluated in different scenarios causing different boundary conditions. Moreover, simulation modeling enables the evaluation of plans using real maps which not only makes the driving distances more accurate but also allows visual analysis of a created plan (Borshchev 2013).

Castane et al. (2019) developed a similar approach and combined an optimization framework with a simulation model for field service planning. While the classification of the problem as a product-oriented PSS is debatable, the simulation model described in this study lacks consideration for key aspects of use-oriented business models typically associated with PSS, such as time windows and penalties. Additionally, the model does not incorporate the possibility of remote service, highlighting the need for further work.

Thus, a simulation model with specific properties is needed to be utilized as a reliable plan evaluator component for manually or automatically generated plans. The simulation model must consider all relevant PSS-specific aspects, necessitating its development by the PSS research stream. Furthermore, it should be customizable and have the capability to be adapted quickly for use by different PSS providers with varying resource pools and order constellations. The model must also enable the collection of relevant statistics and performance indicators of planned resources, while also allowing the execution of smart services such as remote assistance (Aquino et al. 2023). To address the uncertainties of reality, the model should incorporate stochastic elements.

3 MODELING THE SERVICE PLANNING OF PRODUCT-SERVICE SYSTEMS

To answer the need for a new plan evaluator tool for the operative service delivery planning in PSS, a simulation model was systematically developed following the procedure model in (VDI 3633) which comprises the phases of task definition, system analysis, model formalization, implementation, and experiments and analysis. While the first two phases are covered in the previous section, the results of the model formalization phase are shown in the following subsections.

3.1 Formalizing the Model

Figure 2 visualizes the main classes and their attributes in the operative service delivery planning in PSS in the form of a UML-class diagram based on the descriptions in Subsection 2.2. The blue classes represent the provider side, and the green one the customer. The violet class for the technical asset stands for the tangible product in the PSS. The red classes symbolize the most relevant classes for the operative planning.

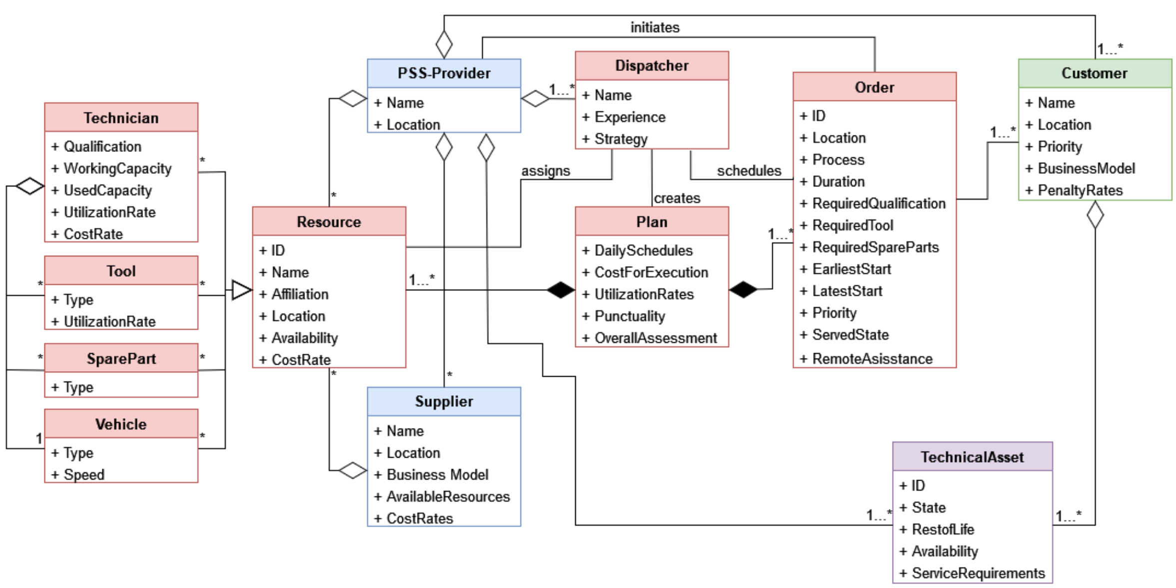

Figure 2: UML-class diagram of the operative service delivery planning

3.2 Identifying the Agents

In the UML diagram above, active and passive objects can be identified. To create a deeper understanding of the system as well as the behaviors of each individual element, the Gaia Methodology, a methodology for the agent-oriented analysis and design by Woolridge et al. (2000), was followed. Focusing on the planning process itself, the main roles in the system are identified as the *Delivery Planner*, *Order Information Holder*, and *Order Deliverer* which leads to an agent-model consisting of the agents: dispatcher agent, technician agent, and order agent. Since tools, spare parts, and vehicles are always managed by a technician, they are not modeled as individual agents, rather their properties flow in the technician agent. For using the simulation model "only" as a plan evaluator component for short-term plans, the design of further agents is not necessary.

3.3 Modeling the Services

Although it is possible to distinguish between different processes such as inspection, maintenance, repair, installation, and the like, from a modeler's perspective, these processes are abstracted to delays of an agent in the model. Consequently, the service processes that need to be delivered in order to fulfill an order are characterized by their duration and complexity whereby the actual duration can be determined by the matching of technician competencies and required qualifications. As mentioned before, not all technicians can perform all tasks (DIN EN 13306). At the same time, there is a possibility to remotely assist an inexperienced technician. This can lead to a virtual increment of the experience, however, cannot substitute an expert self (Aquino et al. 2021). Figure 3 depicts the matching between service process complexity and technician qualification with the resulting durations.

Complexity

Experience	**Basic-Routine Process** Level 1	**Standard Process** Level 2	**Complex Process** Level 3
Novice Technician Level 1	*Duration*	*Duration + 50%*	-
AR-assisted Technician Level 2	*Duration*	*Duration + 20%*	*Duration + 50%*
Expert Technician Level 3	*Duration*	*Duration*	*Duration*

Figure 3: Complexity and Qualification matching

4 IMPLEMENTING THE MODEL

For the model implementation, *AnyLogic University 8.8.2* (Borshchev 2013) was utilized, which allowed agent-based modeling and the incorporation of GIS maps to accurately calculate distances. The developed model comprises three types of agents: *main*, *order*, and *technician* agents. As the dispatcher´s assigning and scheduling functions are of greater relevance than their behavior and they only occur at the model start, these functionalities were integrated into the main agent. The implemented model represents an offline operative service delivery planning for a five-day time horizon. All orders are given at model start-up and consecutively planned by the dispatcher. The model can be used to evaluate a given plan by executing it or to first generate a plan for the given orders and available technicians using simple heuristics and then execute it. For the execution, there were several options modeled. The user can activate the skill factor to make the service delivery duration dependent on the complexity of the order and the qualification of the executing technician. Besides, the user can activate the possibility for remote assistance during service delivery. Another option is to activate the stochastic factor in order to consider uncertainties during service delivery.

4.1 Adaptivity

To ensure adaptivity, the model was designed in such a way that all agents and their parameters are instantiated based on an Excel database. In this way, a user can customize the model easily to his needs.
By changing the entries in the database, the user can determine the quantity of the orders as well as their attributes or the quantity of the technicians and their attributes. This feature makes the simulation model a tool that can be used for any operative service delivery planning in PSS. To increase user-friendliness, the

data input can be done via a user interface developed in Excel VBA. A further development for the future could be the implementation of an interface to the ERP/MES systems of a PSS provider.

4.2 Agents and their characteristics

4.2.1 Order Agent

Figure 4 shows the implemented order agent. On the left side, the parameters defined in the UML-class diagram (Figure 2) combined with the attributes of the customer are implemented in the appropriate types. In addition, the variables *plannedTech* for storing the executing technician and *timeFinshed* for storing the timestamp when fulfilling the order have been added. The state chart in the middle defines the behavior of the agent. The transitions downwards are triggered depending on the advancing time. If an order agent reaches the state **waitingOutofTimeWindow** the system dynamics variable *OutofTimeWindow* on the right side is set to 1. This leads to the activation of the flow *penaltyPerHour*. When the order is fulfilled, the agent goes into state **served** and the flow is deactivated.

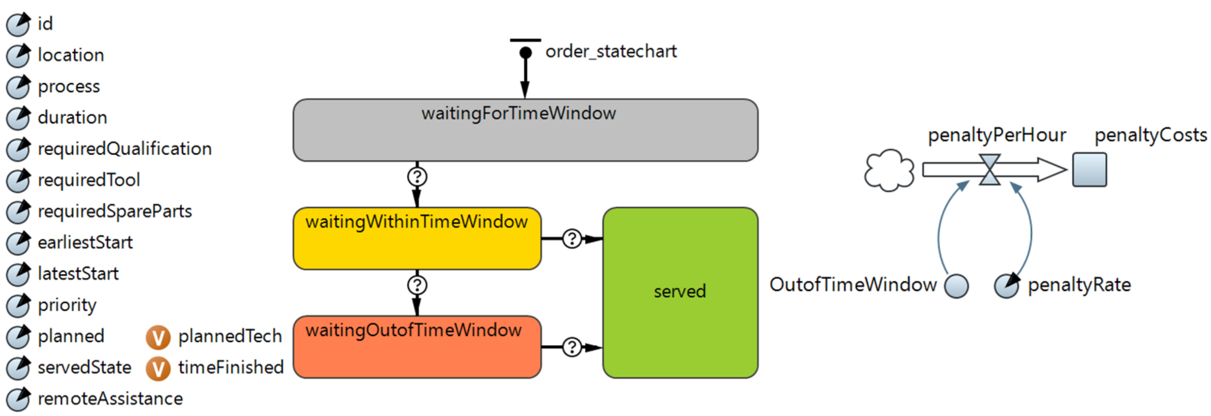

Figure 4: Order agent

4.2.2 Technician Agent

Technician agents are responsible for fulfilling orders by executing a given plan. Figure 5 illustrates the basic characteristics of the technician agent with its parameters on the left and its state chart in the middle, and further variables and collections containing the assigned orders per day on the right side. For reasons of simplification, it is assumed that all technicians have the same vehicle and that the use of vehicles does not cause bottlenecks. Moreover, all technicians have the necessary tools for all service processes. Spare parts were not integrated into the model since their delivery can also be done by logistic companies.

In the following, the logic and behavior of the technician agents are explained in the case that the possibility of remote-assisted smart services is not activated. At the model start and every 24 hours, the event *dailyRouteUpdate* is triggered and the route of the corresponding day is set as *todaysRoute*. Technician agents start in the state **OffWork**. If a technician agent has assigned orders for the day, the time is over 6:00 AM and the earliest start date of the order will have arrived when traveling there, he goes over to the state **Working**. From the first decision branch (1) he follows the arrow downwards and drives to the next customer. If the technician arrives earlier than the earliest start date of the order, he stays in the state **WaitingAtCustomer**. If the current time is later than the earliest start date, the second decision branch (2) is reached without waiting. From here, he takes the arrow to the right and enters the state **DeliveringService**. The servicing time depends on the preferences of the user. Either it is deterministic and delivering services takes as long as specified in the order itself or the skill factor is activated, and a new duration is calculated always based on the properties of each order and the fulfilling technician. Another option is to activate the stochastic factor. In this case, the duration of service delivery is calculated based on probability distributions. When exiting the **DeliveringService** state the *servedState* parameter of the order is set to true and the technician agent reaches the third decision branch (3). If there are more orders to be fulfilled in the collection, the technician agent follows the arrow to the right, reaches the first decision branch (1), and goes through the same states with the next customer. If there is no unserved customer left in *todaysRoute* the technician agent takes the arrow up from the third decision branch (3) and drives to the headquarter. If his working time has not reached 8 hours yet he stays in **IdleAtHQ** and then leaves for **OffWork.**

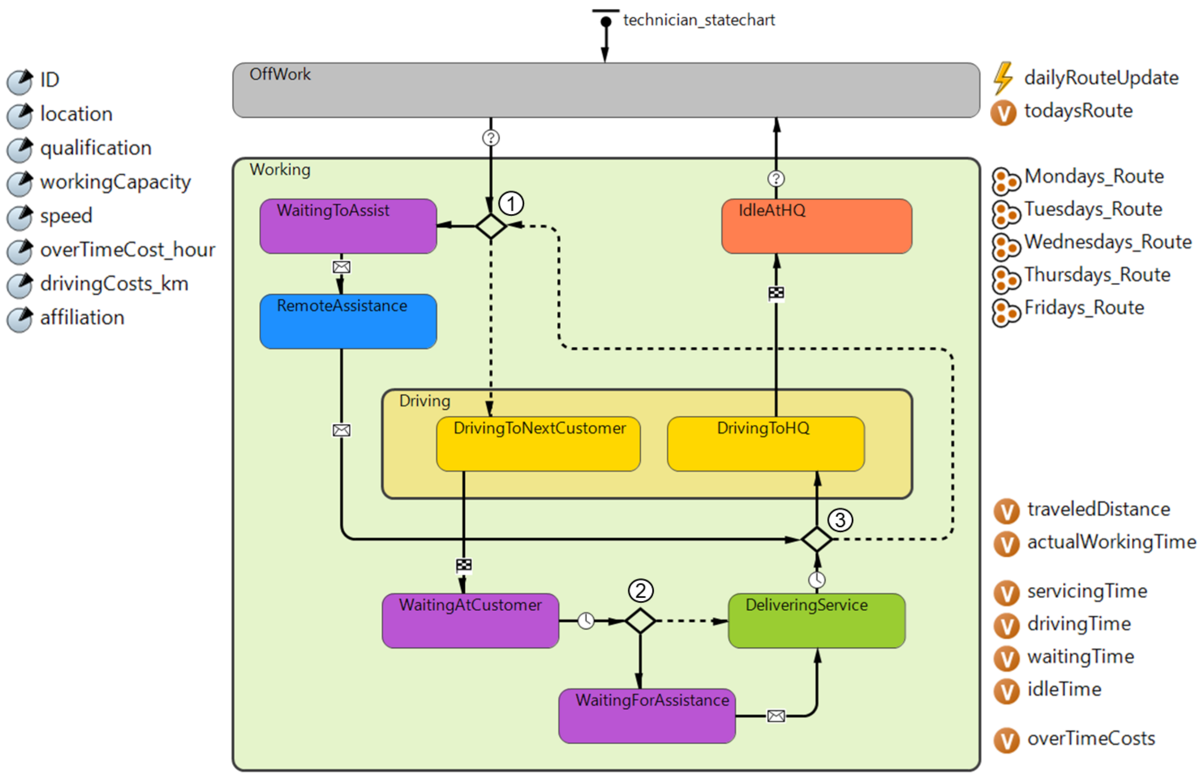

Figure 5: Technician Agent

In the case that the possibility of remote assistance is activated and there are orders planned to be fulfilled with remote assistance, a technician with level 1 qualification (in the following "novice") is paired with a technician with level 3 qualification (in the following "expert") for the same order. At the first decision branch (1), the expert follows the arrow to the left and enters the state **WaitingToAssist** after the novice started traveling to the customer. When the novice reaches the second decision branch (2), he follows the arrow down to the state **WaitingForAssistance**. When entering this state, he sends a message to the expert about his state which leads to the expert entering the **RemoteAsisstance** state and sending back a message to the novice in order to start delivering the service. When the service delivery is finished, the novice sends a message to the expert and both agents reach the third decision branch (3) where the next step for each technician is decided.

4.2.3 Dispatcher Agent

As mentioned above, since only the functionalities of the dispatcher agent were relevant, his functionalities were implemented as functions (Java code) and placed on the main agent. In the model, these functions have the responsibility to iterate over the list of orders and assign them to a technician by adding them to a collection of the respective technician. If the user does not enter a completed plan, the dispatcher functions generate a plan following simple heuristics. Thus, a simple plan generator component was implemented into the model.

One way of dispatching the orders is to analyze the orders regarding their earliest start dates and then add them to corresponding collections for each day following a *First-In-First-Out*-Rule (FIFO). Next, the contents of the collections are allocated to the technicians. During the allocation, it is checked whether the technician can deliver the order by calling the *canDeliver* function of the corresponding technician. This function calculates how much the addition to the working time would be if the order was inserted into his plan. If the maximum working capacity is exceeded with the order, the dispatcher checks the availability of the next technician. Another modeled logic for the dispatching is that the orders first get sorted according to their earliest start date and then allocated to the resources. In the case that the possibility of remote assistance is activated, the dispatcher agent first allocates these orders to a novice and an expert technician and then schedules these so that they are planned at the same time and then allocates the remaining orders.

At this stage of the work, the dispatcher agent was kept simple since the concentration lies in the development of the simulation-based plan evaluator component. In future studies, sophisticated optimization algorithms such as Genetic Algorithms will be implemented for the functionalities of the dispatcher agent by expanding functions and adding Java classes to the model.

4.3 Model Verification

The model has been verified through sensitivity analysis. For this, a user interface has been implemented on the start page of the simulation which enables the generation of plans manually. Multiple users entered different plans and observed model behavior. Any inconsistencies or anomalies identified during the analysis were investigated and improved to ensure a logical and realistic behavior of the model.

5 EXPERIMENTS

5.1 Scenario

To test and verify the developed simulation model, a fictive scenario was created. A randomly generated list consisting of 25 orders serves as a database for a PSS provider located in Bochum, Germany which has three technicians, whereby two of them are novices and the other one is an expert. The orders come from 25 different customers dispersed in a radius of ca. 200 km from the provider and have different earliest and latest start dates. The order durations reach from 1 hour to 5 hours whereby the required qualification is represented as an integer between 1 and 3. While some orders provide a time window of a few days for the service delivery others only provide a few hours. Four orders can be executed with remote assistance.

5.2 Running the model

In automatic planning mode, the dispatcher agent assigns the order to the technicians following the FIFO rule. The dashboard in Figure 6 visualizes the locations of the provider (red building) and the customers (yellow). When executing the model, the states of the technician agents, symbolized by driving trucks on the map, are displayed in the Gantt chart. The evaluation of the entered plan can be taken from the statistics at the right bottom. The screenshot shows the planned values (grey), the results of conventional methods for evaluating plans, and the actual values (blue), the results of the stochastic simulation model. Based on the big differences, it gets evident, that relying on deterministic models can lead to miscalculations. In the example below, there is a difference of more than 10.000 € in only one week. Calculating with deterministic travel and process durations is particularly problematic if during the execution an order cannot be delivered due to delays in the previous one. This highlights again the need for realistic plan evaluation tools.

To enhance the degree of realism, further investigations can explore the deviations between generated plans and the plan execution in a real-world business context, focusing on identifying the most influential factors contributing to uncertainty.

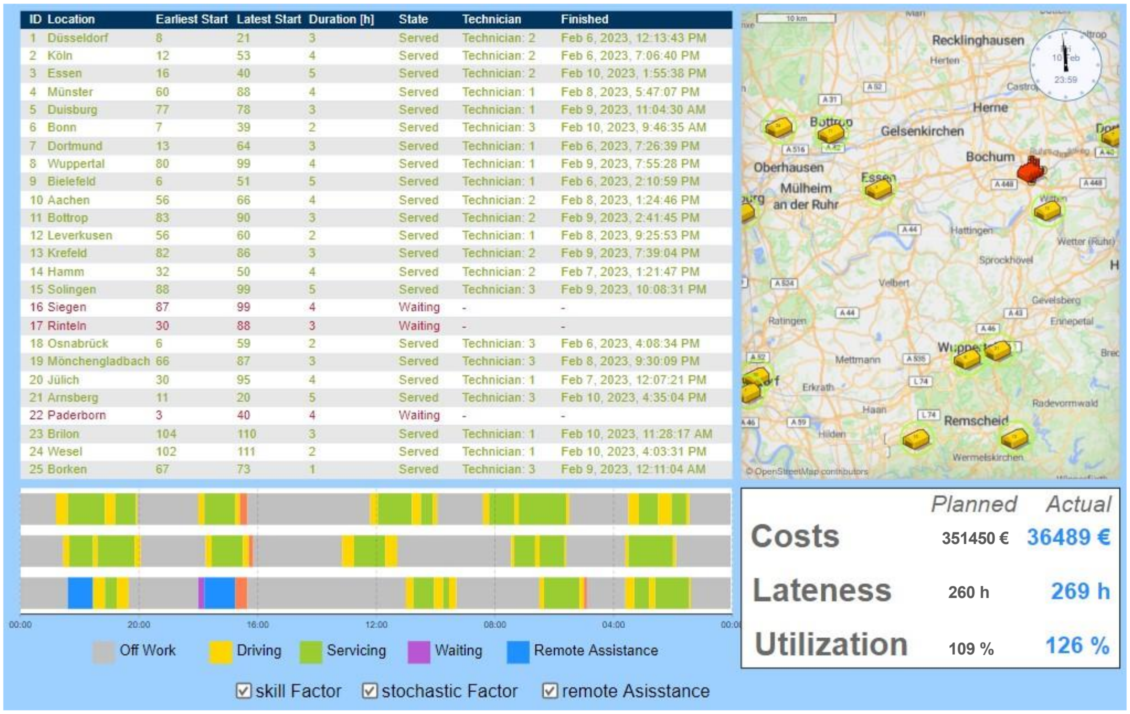

Figure 6: Dashboard of the simulation model

6 CONCLUSIONS AND FURTHER WORK

In this paper, the systematic development of a simulation model for the operative service delivery planning in PSS was presented. The model considers the characteristics of PSS and their business models, is adaptive and easily customizable, allows the execution of smart services like remote assisted service delivery, and is capable of incorporating uncertainties. Thus, the model suits to be used as a plan evaluation tool for operative service delivery plans in PSS. Following the approach of Castane et al. (2019), the developed model could be combined with suited optimization algorithms in order to create a new decision support system. Figure 7 visualizes the concept of such a decision support system.

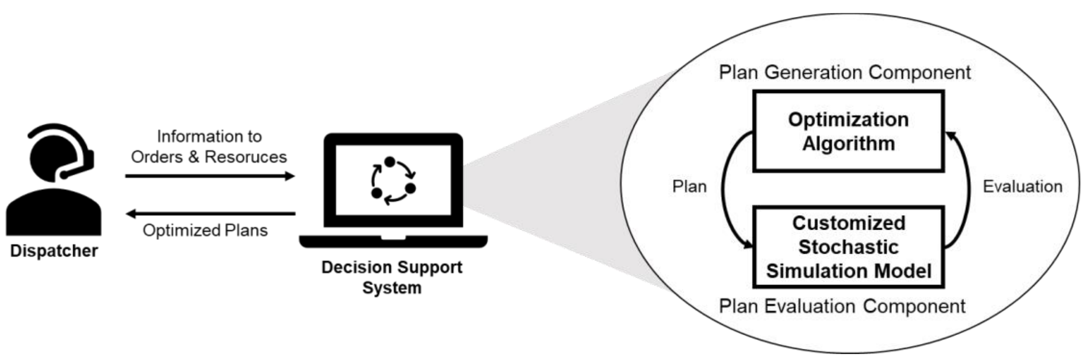

Figure 7: Concept of the decision support system

The model is not free from limitations and provides opportunities for further work. First, the model represents an offline planning model for 5 days neglecting the possibility of an unforeseen urgent order occurring in the middle of the week causing a rescheduling of the plan. Further, the assumption is that the technicians have a 100% first-time fix rate, but this is probably not the case in reality. Consequently, the model needs to be validated by practitioners to increase its accuracy. In a further step, the model could be connected to the ERP/MES systems of a company in order to obtain a digital shadow or twin for the operative service delivery planning in PSS.

Another opportunity for further work lies in the integration of the developed work into a broader simheuristic framework like in Juan et al. (2022). There, the authors presented a three-stage procedure model for combining deterministic optimization algorithms with stochastic simulation models in order to receive elite stochastic solutions with probabilistic information.

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