Towards a Technician Marketplace using Capacity-Based Pricing

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Abstract

Today, industrial maintenance is organized as an on-call business: Upon a customer's service request, the maintenance provider schedules a service technician to perform the demanded service at a suitable time. In this work, we address two drawbacks of this scheduling approach: First, the provider typically prioritizes service demand based on a subjective perception of urgency. Second, the pricing of technician services is inefficient, since services are priced on a time and material basis without accounting for additional service quality (e.g. shorter response time).

We propose the implementation of a technician marketplace that allows customers to book technician capacity for fixed time slots. The price per time slot depends on the remaining capacity and therefore incentivizes customers to claim slots that match their objective task urgency.

The approach is evaluated using a simulation study. Results show the capabilities of capacity-based pricing mechanisms to prioritize service demand according to customers' opportunity costs.

1. Introduction

1.1 Motivation

Industrial maintenance—often being outsourced—is still the backbone of the industrial service business today. When industrial machinery needs to be maintained, repaired, or overhauled, customers (the manufacturers operating the machine) request a maintenance job from a service provider. The provider performs the service at a suitable time and prices it according to a specific pricing approach: the most common ones being "time and material spent" or according to a "long-term maintenance contract".

Recently, the perception of industrial maintenance has changed. Having been considered as a "necessary evil" in the past, efficient maintenance is now seen as a competitive advantage [1], as maintenance costs account for around 28% of total production costs [2]. Due to this perception, maintenance providers are in need for competitive service delivery, of which the performance is greatly influenced by an efficient scheduling of jobs. That is, providers need to correctly allocate spatially distributed tasks to spatially distributed technicians. The process of allocating tasks to technicians is subject to many constraints, for example, the consideration of skills, customers' and technicians' locations, and, very important, by the priority of the service demand. This task of allocating service demand to technicians is called dispatching and typically performed by human dispatchers.

1.2 Problem Formulation and Research Objective

Today, the dispatching of industrial maintenance underlies two major drawbacks:

First, dispatchers do not follow clear rules on how to prioritize service demand in times of technician shortage (i.e. situations during which the urgent demand cannot be met with the available technician capacity). One prominent approach for dealing with this problem is to prioritize tasks based on the first-come-first-serve (FCFS) principle. Thus, requests are prioritized according to their time of arrival. Another common approach is to prioritize requests based on customer segments: customers who pay a periodic fee to receive higher service request are prioritized over regular customers. In practice, those customers are often referred to as *premium customers*. Our findings from practice, however, do not support the correct application of prioritization methods. Often, prioritization does not follow clear rules, as it is highly influenced by human opinion. For example, customers causing the highest trouble (e.g. by often calling the service provider) are

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prioritized just because they indicate urgency and claim high priority. To address such problems, there is a need to develop an objective and transparent prioritization method for field technician scheduling.

Second, pricing of maintenance services typically follows a cost-plus pricing mechanism. This means that service providers set prices according to their costs with an additional margin for their profit.

The impact of these two drawbacks can easily be shown with a simple example: There are three broken machines that are in need for an urgent repair (i.e. service demand). One machine (customer A) is operated in an advanced just-in-time production system and its downtime results in the shutdown of the entire production line. The second and third machines (customers B & C) are part of flexible production systems in which a short machine failure can be compensated (e.g. by the usage of buffers). Given those three cases, it is highly likely that customers have varying willingness to pay (WTP) for an immediate repair as indicated in Figure 1. Today, those three machines would be treated equally and the dispatcher decides which machine would be served first. Therefore, prioritization is not done under consideration of the WTP of the customer (and therefore the real urgency of the task). Second, as shown in Figure 1, the single service price allows customers to realize a high consumer surplus (grey area). This is a known issue for cost-plus pricing in scenarios in which providers face high fixed and low variable costs [3].

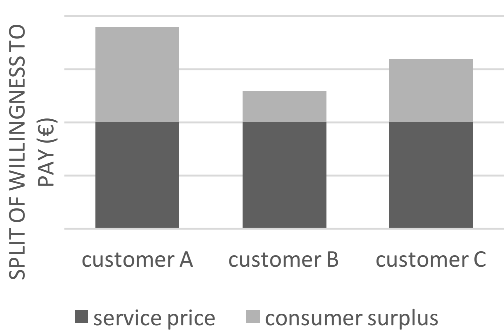

Figure 1: Customer Surplus

The objectives of this work are two-fold: First, we aim to develop a pricing strategy that results in objective task prioritization by allowing customers to self-signal their task urgency through their WTP. Second, we propose a more efficient market solution by pricing maintenance services based on the added value created for the customer. Hence, the developed solution simultaneously increases provider's revenue and results in objective task prioritization by exploiting customer's signaling effects.

2. Fundamentals and Related Work

In this section, we first introduce fundamentals of industrial maintenance. Second, we give an overview on field agent scheduling, before, third, introducing field agent scheduling. Fourth, we introduce relevant literature on pricing of industrial services, before, finally, introducing research on the estimation of costs of downtime.

2.1 Fundamentals of Industrial Maintenance

Manufacturers of industrial machinery commonly support their customers with supplementary maintenance, repair and overhaul (MRO) services. Geraerds [4] defines these services as "[...] all activities aimed at keeping an item in or restoring it to the physical state considering necessary for the fulfilment of its production function". Service in the context of industrial maintenance can further be categorized as (a) plannable, preventive services (e.g. machine installations, periodic maintenance, overhaul), and (b) unplannable, corrective services (e.g. breakdown). Manufacturing companies generally provide these services through distributed field service technicians. The efficient utilization of their limited capacity is an important success factor for their service departments [5].

The process of industrial maintenance is traditionally structured as follows: Once a machine requires service the customer manually opens a service request. Thereafter, the service provider tries to identify the required service activities to be performed which approximately determines the priority of the task (relatively to all other unfulfilled requests), the expected service duration and the required technician qualifications. When this information is known, the task is handed over to dispatchers. Dispatchers assign spatially distributed service demand to spatially distributed field technicians. This is a highly complex task and will be further explained in the next section. Once assigned, the task service is delivered.

Traditionally, such services are priced based on their required time and material spent. Recently, however, customers increasingly demand agreements that are closer aligned with their needs [6]. Examples of such long-term engagements are full-service (e.g. [7], [8]), availability- (e.g. [9], [10]), or performance- (e.g. [11], [12]) based maintenance contracts. The contracted service levels of such agreements can theoretically act as a proxy to prioritize the service demand of customers in the dispatching process. However, expert interviews have shown a poor consideration of those requirements in day-to-day dispatching decisions. Therefore, generally customers pay standardized prices disregarding individual circumstances [7].

2.2 Field Service Scheduling

Dispatching is not limited to industrial maintenance, as other industries have similar problems (e.g. transportation in health care, telecommunication technician services, etc.). However, each industry introduces its own characteristics. Whereas some industries rely on highly automated dispatching systems, dispatching in industrial maintenance is often done by human dispatchers with little technical support.

Dispatching is done under consideration of multiple constraints. For example, dispatchers must consider technician skills, task priority, routing, and working times during decision making. In addition, industrial maintenance underlies much uncertainty. First, maintenance providers do not know future service demand. Second, even if they are aware of a service task, they cannot predict their duration exactly. In practice, dispatchers have different strategies to deal with uncertainty, most of them being based on individual experience.

Field service scheduling is explored in a variety of interconnected research fields. The domain of operations research focuses on algorithmically solving vehicle routing problems—a superset of field service planning. Based on a literature review of peer-reviewed taxonomies, Vössing [13] provides an overview of the many facets of vehicle routing problems addressed in the operations research domain. Additionally, he outlines how the complex, dynamic, and stochastic real-world field service planning motivates the need for novel planning approaches.

Obviously, both the transactional process and the established business models of industrial maintenance highly limits the short-term flexibility ideally required to quickly response to urgent customer requests. This is further complicated as dispatchers simultaneously pursue two contradictory goals: high technician utilization and flexible capacity for short-term service demand. Today, many dispatchers apply individual, loosely defined dispatching strategies. Even though scheduling algorithms are available, most dispatchers follow simple strategies as outlined by Hill [14]. Especially the prioritization of service requests has little guidelines and oversight, therefore many companies can improve their dispatching processes with advanced prioritization concepts.

2.3 Pricing Strategies for Industrial Services

Previous research has shown that industrial service pricing is more challenging than the pricing of industrial products [15].

Three main dimensions of pricing are traditionally researched in the literature. First, pricing objectives (e.g. maximize profit or maximize market shares) that define the provider's pricing goals. Second, pricing methods (e.g. cost-, competition-, and value-based pricing approaches) that describe the logic how prices are being determined. Third, pricing policies (e.g. list prices, differentiated pricing, or yield management) that define the way prices are presented to the customer.

A literature review by Avlonitis and Indounas [16] shows that most industrial services are priced based on the cost-plus (cost-based pricing) or the market-based (competition-based pricing) approach. Further studies in industrial pricing include contributions on the success of service pricing companies and their pricing approaches [17], and in which environment industrial service providers adopt pricing policies, such as skimming, penetration, and competitive pricing [18]. Finally, Indounas [19] analyzes how the choice of a pricing strategy influences industrial service provider's performance.

2.4 Costs of Downtime

Around 80% of industrial companies are unable to accurately predict their cost of downtime. Usually, enterprises underestimate their costs significantly such that the actual costs of downtime are two to three times higher than expected [20].

Researchers differentiate between direct and indirect costs of downtime. Direct costs of downtime are costs that can directly be associated with the repair of a broken asset (i.e. time and material spent for repairing the asset). Indirect downtime costs are consecutive costs of an asset's failure due to idle labor force, opportunity costs due to reduced production quantity, or even monetarized loss in reputation.

So far, research has focused on determining the costs of downtime for individual machine failures, as, for example, in Fox et al. [21] and Vegunta and Milanovic [22]. In addition, these studies on specific use-cases are supplemented with a qualitative studiy on how companies deal with the determination of costs of downtime [23].

The estimation of downtime costs prior to a machine failure is only approached by Wolff and Schmitz [24]. Their work presents a model for calculating the costs of downtime based on production losses for simple production systems. They formulate the need of further research on the estimation of downtime costs.

3. Design of the Marketplace

3.1 Introduction to the Marketplace

This work proposes the concept of a marketplace to realize both research objectives: The marketplace gives customers the possibility to book technician capacity for predetermined time windows. Hence, the marketplace gives customers complete control about the time at which field service technicians provide the requested service. In addition, by using price variations the marketplace will result in higher revenue for the provider. The following analysis focuses on the dispatching of urgent service requests only (i.e. breakdowns). In addition, we assume that industrial manufacturers want their equipment repaired as soon as possible, thus ignoring any additional influence factors.

When maintenance is required, customers can search for technician capacity on the marketplace. Prior, customers must state the location the service is required at, the service duration, and the required skillset.

	Technician				Possible Service Time i
Time Slot j	#01	#02	#03	#04	
08:00 - 08:15	(T)				
08:15 - 08:30	(T)				
08:30 - 08:45	(T)				1
08:45 - 09:00					2
09:00 - 09:15					3
09:15 - 09:30					4
09:30 - 09:45					5
09:45 - 10:00	customer A	(T)			6
10:00 - 10:15		(T)			
10:15 - 10:30					
10:30 - 10:45					
10:45 - 11:00		customer B			
11:00 - 11:15	(T)			(T)	
11:15 - 11:30	(T)		(T)	(T)	
...	...	...	...	...	...

Figure 2: Exemplary Current Technician Schedules

At all times, the marketplace holds a valid current schedule for all technicians, as exemplarily shown in Figure 2. We see that daily work times are split into a series of time slots of predetermined length (here 15 minutes). Travel times are denoted by *(T)*. As shown, any technician activity (e.g. travelling, repair) needs to start and end with time slots but can include a series of them. If needed, activities are extended to the next time slot. Hence, in this case, a travel time of 17 minutes requires two consecutive time slots.

Based on the specified service request of the customer and the current technician schedules, the marketplace searches for possible time slots to perform the service. For example, Figure 2 shows potential times to perform a requested service of 90 minutes (hence 6 time slots) by the dotted areas. Technician #02 cannot perform the service, since the additional required travel times would exceed his available time. Using available technician capacity, possible service times are identified that each have a price—but no technician—associated to them. Here, there are six possible service times—as shown in Figure 2 in the *Possible Service Time i* column, with prices $p_{s,i}$, $i \in [1, 2, \ldots, 6]$ associated to them. As the service duration is determined by the task to be performed, possible service times are identified by a unique start time t_s and the price p_s associated with it. The price p_s is the price for the service to be performed at the given time. Hence, the marketplace provides the customer with the list of possible service times and associated prices as shown below.

$$[(t_{s,1}, p_{s,1}), (t_{s,2}, p_{s,2}), \ldots, (t_{s,n}, p_{s,n})]$$

For the given example, the possible service times given to the customer are:

$$[(08{:}30, p_{s,1}), (08{:}45, p_{s,2}), (09{:}00, p_{s,3}),$$
$$(09{:}15, p_{s,4}), (09{:}30, p_{s,5}), (09{:}45, p_{s,6})]$$

Once possible services times are transmitted, customers freely decide at which of the possible service times the service will be fulfilled. A rational customer chooses the earliest possible service time that has a price smaller or equal than his WTP—and as explained later—therefore minimizes his total costs. Once a service time is chosen, the marketplace assigns the task to an available technician for the given time and bills the customer according to the price associated with that service time.

Following the above explanation, the marketplace consists of the following modules: First, the input module that allows customers to provide required data for the service request (e.g. service duration, location, and required skillset). Second, the marketplace has an algorithm that identifies possible service times for the required service. Third, the marketplace has a mechanism to determine prices associated to possible service times, and, finally, the marketplace needs the capability to reserve the chosen technician capacity based on the previously proposed service times.

3.2 Customer's Willingness to Pay

In this section, we want to explain how the WTP of a customer can be modelled. For the following, we assume that customers want their machinery repaired as soon as possible and act as rational decision makers, thus try to minimize their own total costs.

As introduced in the related work section, the customer faces two cost categories in the case of a machine breakdown, namely direct and indirect downtime costs. In this work, we limit direct costs to labor costs (ignoring other aspects such as material costs, as they must be paid regardless of service time and thus, are a fixed add-on that do not influence decision making) and indirect costs to opportunity costs arising from reduced production output (lost revenue). From now on, we refer to direct costs as service costs c_s, and indirect costs to opportunity costs c_o. Using this terminology, the total costs c_t for a machine breakdown are calculated as shown below.

$$c_t = c_s + c_o$$

The marketplace provides the customer with a set of possible service times. For each possible service time i, the customer calculates the total costs $c_{t,i}$. The opportunity costs $c_{o,i}$ are determined by the sum of opportunity costs that are incurred over time until the machine is fixed. Opportunity costs can be calculated by fixed costs based on time-units or based on the current production plan. However, the estimation of opportunity costs is not part of this work. The service cost $c_{s,i}$ is the price of the possible service time i. The determination of the service costs $c_{s,i}$ is explained in the following section. The customer now uses the total costs $c_{t,i}$ of the possible service times to prioritize them according to his point of view.

Knowing the total costs $c_{t,i}$ for all possible service times i, the customer is willing to pay as much as the price of the possible service time i that has the lowest total costs.

3.3 Pricing of Service Times

Using the marketplace, the provider aims at selling different services to different customer segments. For example, customers with high opportunity costs and customers with medium opportunity costs might both represent a segment. In this case, the services are characterized by different response times. Customers with high opportunity costs are addressed with services with a short response time, whereas customers with low opportunity costs are addressed with services with longer response times. Of course, the services are priced differently. In other words, the provider aims at selling a certain amount of capacity to different segments at different times ahead of time.

As the provider does not know which customer belongs to which segment, he needs customers to signal their segment belonging. Customers of the different segments have different WTPs due to their different opportunity costs. Hence, it makes sense for the provider to differentiate segments by the pricing policy. Using capacity-based pricing mechanisms, the price of a service depends on the remaining technician capacity at that time, what means that booking of technician capacity at peak times is more expensive than the booking of technician capacity during off-peak times. Unfortunately, as service times are a series of consecutive time slots, available technician capacity does not necessarily remain constant during the entire service time (see Figure 1: technician availability changes between 09:00-09:15 and 10:30-10:45). Therefore, we propose to determine the price of a possible service time i ($p_{s,i}$) based on the sum of prices for the time slots j the possible service is composed of. Given individual prices $p_{ts,j}$ for time slot j, the service time price for alternative i is calculated as shown below.

$$p_{s,i} = \sum_{j \in i} p_{ts,j}$$

However, we did not explain how the price $p_{ts,j}$ of a time slot j is determined. For individual time slots, we are able to calculate technician availability. Depending on the remaining available capacity, the time slot price p_{ts} is either discounted or increased. Those effects are realized using a base price p_b that is multiplied by a capacity-based factor. The capacity based factor can be modelled using a function, such that in short, the price $p_{ts,j}$ of time slot j is calculated as shown below.

$$p_{ts,j} = f\left(c_{max,j}, c_j, \ldots\right) * p_b$$

Here, $c_{max,j}$ is the maximum technician capacity during time slot j and c_j represents the remaining technician capacity during time slot j. If needed, the pricing function can incorporate additional parameters as denoted by "…". p_b denotes the base price for the demanded service.

At this point we want to clarify the available capacity. Available technician capacity is defined as technician time that can be used to do revenue-increasing tasks, hence that can be used to fulfil additional service tasks. Therefore, travelling technicians, even though they are currently not performing a service task on a customer's site, are accounted for as being unavailable. Using Figure 1, for example, the technician capacity available during the time slot from 9:00-09:15 is 75%, whereas the time slots from 10:00-10:15 and 10.15-10:30 both have an available technician capacity of 50%, even though in the first one, one technician is marked as travelling.

Relating to the related work on industrial service pricing, the pricing objective of the proposed approach is a higher revenue for the service provider and the task prioritization by customers based on a monetarized point of view. The pricing method is value-based, as the base price p_b is oriented on the mean customer added value by a repair. Adaption to the customer segment is achieved by the multiplier. Finally, the pricing policy used on the marketplace, capacity-based pricing, is a combination of service demand based pricing under the consideration of customer price.

It is important to note that any customer is still able to book service capacity at any time desired. However, the customer needs to have a WTP higher than the service price demanded. Therefore, the service price p_s is used as an approach of self-segmenting customers in urgency categories. In addition, the effectiveness of the pricing function on the desired research objective, the determination of the real urgency of a task, increases with the number of segments. Ideally, every customer is characterized by his own customer segment. However, it is doubtable that this is practically feasible.

4. Evaluation of the Marketplace

4.1 Methodology

The impact of a technician marketplace is evaluated using a simulation experiment. From the many simulation approaches available, discrete event simulation fits our case best. Activities can be discretized to certain events, for example, the working time can be modelled as an event it begins at and as an event it is finished. In between, the status of neither the technician, nor the machine changes. The simulation is implemented in Python using the SimPy[1] framework. Using simulation techniques to evaluate effects of changes on field service scheduling is a common approach and has already been applied by multiple researchers (e.g. [25], [26], [27]). A comprehensive review of simulation in maintenance (including scheduling) is given by Alrabghi and Tiwari [28].

The simulation experiment is structured as follows: There are two scenarios, A and B, that only differ in the time slot pricing function. Scenario A represents industrial maintenance as done today under FCFS dispatching. This means that a repair is scheduled as soon as possible for a fixed price. Scenario B represents the industrial maintenance market using a technician marketplace with a capacity-based price function. The determination of the pricing function is explained in a following section.

To achieve higher generalizability of results, both scenarios are simulated fifteen times, each time having different random seed values (hence introducing new pseudo-randomness). One simulation run covers an entire year, during which the first three month are regarded as settling time and not included in analysis.

4.2 Introduction to the Simulation Model

The simulation consists of manufacturing units that fail over time. Once failed, the equipment (the customer) demands available repair times (i.e. possible service times) along with their prices. As mentioned before, the customer then decides on the time window based on rational decision making, hence the time window minimizing total costs. Prices for time windows are determined following the defined price function. Once the repair time window is chosen, the manufacturing equipment remains broken and is reset once a technician arrived and completely performed the repair work. For simplicity, machines are assumed to work continuously (e.g. three shifts) and that technicians work from 8:00 until 16:00. All days are assumed to be normal working days (no bank holidays or weekends).

Table 1: Category's Opportunity Cost Distribution Parameters

	high	medium	low
μ	5.0	2.0	1.0
σ	1.2	0.5	0.25

As introduced before, we assume that different customers have different WTPs. As the WTP is influenced by the opportunity costs c_o of a customer, we distinguish between three groups of customer categories during the simulation. First, we have customers that have low opportunity costs c_o. Second, and third, we have customers with medium and high opportunity costs. The opportunity costs per time slot of a category follow a normal distribution with the distribution parameters as shown in Table 1. Those prices may be interpreted as absolute values or as a factor of the multiple of a mean opportunity cost over all customers.

To model travel times correctly, the simulation uses a set L of 5000 locations. For each pair of location $o, j \in L$ and $o \neq j$, we determined a random and symmetric travel time. The travel times (in minutes) between each pair $o, j \in L$ follow a $N(60, 15)$ distribution.

Additionally, the parameters shown in Table 2 were used for the simulation model. The number of machines and technicians are chosen such that—assuming the given mean time until failure after repair and around two tasks performed per technician per day—the technician capacity is sufficient to perform the total service

[1] https://simpy.readthedocs.io/en/latest/

demand. The mean time until failure after repair of machines follows an exponential distribution with a mean value of 28 days. The lead selling time, set to four days, is the time horizon that technician capacity can be booked ahead in time. Finally, the repair duration is set to two hours and 30 minutes, technicians work for eight hours a day and a time slot has a duration of 15 minutes.

Table 2: Simulation Parameters

Parameter	*Value*
number of technicians	10
number of machines	500
mean time to failure after repair	~ exp(λ) with λ = 28 days
lead selling time	4 days
repair duration	2 hours 30 minutes
working day length	8 hours
time slot duration	15 minutes

The simulation model includes the following simplifications: First, according to the simplification specified earlier, we ignore any technician skill restraint, hence, any technician can perform any repair. Second, due to the proof-of-concept character of this study, we assume all repair works to be of equal length. Third, we do not take disruptions into account. Therefore, both, travel and service duration times are deterministic which results in a robust schedule. Fourth, we only differentiate between three groups of customers having different opportunity costs.

4.3 Design of the Pricing Function

For reasons of simplicity, we assume that $p_b = 1.0$. The pricing function for scenario A, representing simple FCFS prioritization, is constant and set to 1.0. Therefore, in scenario A, any time slot j is priced such that $p_{ts,j} = 1.0$ and therefore does not vary. By doing so, we assure that any customer books technician capacity as early as possible, as prices remain fix—regardless of the time of service—but opportunity costs, and with the opportunity costs also the total costs increase over time.

Assuming complete information for designing the pricing function for scenario B, the provider wants to sell services to three customer segments: First, the provider sells cheap capacity for customers having low opportunity costs, and, second and third, selling average and highly priced technician capacity to the customers of the medium and high opportunity cost segments, respectively. The services targeting the different segments vary in their response time. Whereas short response time services are usually priced at a high level due to a low remaining technician capacity, long response time services are much cheaper as they are meant to be sold further ahead.

The time between the moment of booking and task action differs for the three segments. High priority customers will book shortly before the task action, whereas low priority tasks will be booked earlier on. Ideally, the provider wants to sell capacity to the different segments according to their relative sizes (in this case one third each). Anticipating the different time lag between booking and service time of segments, the provider sells capacity between 100% and 66% at a price suitable for customers of the low opportunity cost segment, capacity 66% and 33% at a price suitable for customers of the medium opportunity cost segment, and the final capacity is sold at a price suitable for customers of the segment having high opportunity costs.

Setting $p_b = 1.0$, the time slot prices in the simulation model are calculated as shown below, with a_j being the slot availability.

$$p_{ts,j} = \begin{cases} 5;\ 0.00 \le a_j < 0.33 \\ 2;\ 0.30 \le a < 0.66 \\ 1;\ 0.66 \le a_j \le 1.00 \end{cases}$$

$$\text{with } a_j = {}^{c_j}/_{c_{j,max}}$$

By setting those prices, customers are in need to determine when to book a required technician capacity. Those prices will incentivize customers to book technician capacity according to their segment. For example, a customer from the low opportunity cost segment will not book technician capacity at times during which capacity is already rare. Instead, the customer waits for the first capacity available that is meant to be sold to the low opportunity cost segment. Accordingly, a customer of the high opportunity segment will always book technician capacity at the first possible time slot available. If the customer waited longer, the opportunity costs will increase proportionally with the gain in lower service price.

Hence, by setting the prices according to the opportunity costs, the provider incentivizes the desired behavior of customers to self-signal which segment they belong to and the desired task prioritization.

4.4 Experiment Results

For evaluation, we decide on using the following performance indicator: First, we want to compare the provider revenues of the two cases. Second, we are interested in the response times for service requests of the different customer segments. Third, we also want to know whether technician utilization changes between the two scenarios. Finally, we also log the overall sum of opportunity costs. Table 3 shows the mean values of the simulation runs for those performance indicators for scenarios A and B.

Table 3: Simulation Experiment Results

Performance Indicator	*Scenario A (FCFS, constant price)*	*Scenario B (Capacity-Based Pricing)*
Technician Utilization	86.00 %	85.99 %
Revenue	64086 €	130543 €
Mean Response Time (All Segments)	14.06 hours	14.35 hours
Mean Response Time (Low-Segment)	14.10 hours	14.81 hours
Mean Response Time (Medium-Segment)	13.92 hours	14.46 hours
Mean Response Time (High Segment)	14.15 hours	13.78 hours
Overall Opportunity Costs	718288.62 €	711308.81 €

Looking at the service provider's revenue, we see a drastic change between the two scenarios. In scenario B, the service provider realizes twice as much revenue as in scenario A. Of course, this must be seen with regards to the different pricing function. Having seen the time slot prices in the different scenarios it is no surprise that revenue is doubled in scenario B. Alone the time slot price for the final third technician capacity is 5 and therefore five times higher than the time slot price in scenario A. However, it is important to note that for both scenarios the same WTP calculations were used, again, demonstrating the effect of perished customer WTP.

Talking about service response times (the time between the service request and the technician arriving on-site) we note only minor, but yet important, changes. First, the overall response time increases in scenario B by around 0.3 hours (around 18 minutes) compared to scenario A. Second, more interesting, however, are the changes in the customer categories' response times. In scenario A, as formulated in the problem description, there is no ordering according to the customer's costs of downtime. By chance, customers with the highest opportunity costs are prioritized the lowest, indicated by the highest response time. In the long run, however, the response times of the three customer segments should be equal. This deviation is caused by the characteristics of a simulation model only testing individual cases. In scenario B, the response times are ascending with descending opportunity costs, therefore indicating the desired results: Customers with high opportunity costs are prioritized higher than those with low opportunity costs. This behavior is explained by the usage of the capacity-based pricing function. Customers of the high segment are willing to pay a higher price for a service and therefore receive an early response time, whereas the WTP of customers of the low segment is too low to book at peak times. Instead, they book technician capacity at cheaper prices further ahead, therefore resulting in a higher downtime cost. We do want to note though that the response times did not change in "favor of" all customers. Especially the customers with low opportunity costs face higher response times in scenario B than in scenario A while paying the same price for the service. However, the observed effects in response times are exactly the desired outcome and meet the second research objective of task prioritization based on actual (and not claimed) task urgency. The overall technician utilization (sum of travel and repair times) does not change between the two scenarios, as we did not change the ratio of technicians and tasks but only the prioritization (i.e. the ordering) of tasks. Finally, we also see that the overall opportunity costs—the sum of all opportunity costs—decreases by around one percent. This is not much, but still, indicated that due to the shift in task priority the overall opportunity costs are reduced.

Overall, the research objectives of first, using pricing mechanisms to prioritize service tasks correctly, and, second, increasing provider revenue, are met. However, we also note that the overall response time over all customers increased along with increased service costs.

5 Future Challenges

The marketplace, as introduced above, faces the following future challenges:

First, customers are in need for support tools to estimate their required technician capacity correctly. In the situation of a repair, for example, customers need to determine the duration and skillset of technician capacity required.

Second, providers must find a way of dealing with wrongly booked technician capacity. For example, a customer might believe that a repair takes two hours, books capacity according to that, however, the repair turns out to take three hours. This problem will occur and needs to be dealt with. Intelligent machinery, however, helps reducing those occurrences by providing additional information.

Third, the question on proper reassignment needs to be addressed. Even if the provider cannot change the start and end times of a service, they can assign it to other technicians and therefore optimize technician routes.

Fourth, the identification of possible service times is a highly interesting task. Providers must ask themselves the question how much flexibility they want to allow when searching for possible service times. For example, providers might anticipate reassignment already at the point of service time proposition.

Fifth, the determination of a suitable pricing function needs to be researched further. Future work, for example, could investigate more advanced pricing methods by using real-time data.

6. Conclusion and Future Work

6.1 Contribution

The presented work proposes the implementation of a technician marketplace that is used by industrial maintenance customers to book technician capacity when needed. In addition, we propose the application of capacity-based pricing mechanism.

This work contributes to research in the field of industrial maintenance. In detail, the following contributions are made: First, the work identifies inefficient pricing mechanism in industrial maintenance and stresses problems in the prioritization of service request in dispatching in practice. Second, a model on estimating industrial maintenance customer's willingness-to-pay (WTP) in case of a machine breakdown is developed. Third, this work suggests the implementation of a technician marketplace that is used by customers to book technician capacity when needed. Fourth, by applying capacity-based pricing, the marketplace yields a solution that results in a higher revenue for the provider, and, fifth, a transparent approach of prioritizing service requests according to their opportunity costs for the customer. Sixth, the approach is evaluated using simulation.

For customers' decision making, this work introduces a model on estimating customers' WTP for a repair by assuming their rational decision making. Customers minimizing their overall costs that are calculated using service prices and costs of downtime.

The marketplace proposed offers customers to self-select service times according to their WTP. Thus, customers signal the true urgency of a service request. Consequently, the service provider does not need to prioritize tasks on subjective perception anymore.

The marketplace—evaluated by using three segment of opportunity cost customers (high, medium, and low) —and the newly introduced pricing mechanism result in an overall longer response time of around 18 minutes compared to simple first-come-first-service dispatching. However, looking at customer segment's response times, we see that capacity-based pricing results in customers with high opportunity costs having shorter, and customer with low opportunity costs having longer response times. Therefore, the desired effects of task prioritization based on opportunity costs is achieved. In addition, technician utilization remains constant at a level of 86% whilst the second research objective, a more efficient service pricing, is met. The provider's revenue is doubled by reducing the consumer surplus.

6.2 Limitations and Future Work

The presented work has the following limitations: First, due to the introduction of the novel approach, many aspects are kept simple or are ignored and therefore result in additional challenges to face. Those aspects have already been mentioned in chapter five.

Second, following current trends, especially a fine-tuned pricing function using real-time data to determine time slot prices is an extension to the presented model.

Third, we assumed that customers require an immediate repair. However, there might be other methods of assessing customer's choice of service time.

Fourth, using an evaluation based on simulation, our work is subject to common limitations of simulation studies. For example, parameters are based on expert interviews. In the future, simulation parameters should be based on quantitative data.

Fifth, other pricing objectives might be worthwhile considering. For example, providers might try to maximize their revenue for repair tasks by auctioning their capacity. This implies, however, that planning happens just-in-time.

Sixth, this work is limited to corrective repair strategies. We assumed that customers want their equipment repaired as soon as possible. However, emerging trends in maintenance (e.g. predictive maintenance) might result in different scenarios. So far, preventive services as well as periodic overhaul or machine installation are not included in the proposed marketplace model. Those additional services need to be addressed in future work and represent an important extension of the proposed model. When including those services, it may be worthwhile to evaluate the application of revenue management techniques. By applying revenue management, providers can actively steer service demand and therefore, for example, incentivize optimized technician routes.

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