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Incentive system to smooth out fluctuations in demand

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Abstract

The global market is influenced by multiple factors such as market trends, cultural dynamics, and geopolitical uncertainties. In this context service providers often face volatile demand patterns leading to sub-optimal capacity utilization. This approach presents an incentive system to smooth out fluctuations in demand and to enhance service provider efficiency. This system computes optimal service prices based on projected capacity utilization. By including insights from past orders and demand forecasts, the algorithm facilitates proactive price adjustments to adapt to changing market dynamics. To implement this system effectively, seamless integration within the service provider's digital infrastructure is essential. This involves establishing standardized Asset Administration Shells to enable the exchange of critical information and the execution of process-related services. This ensures interoperability with existing components, fostering a cohesive operational environment. The approach is validated within the infrastructure of a medium-sized service provider and demonstrates its potential for wider industry adoption. By leveraging dynamic pricing mechanisms and digital infrastructure, the proposed incentive system offers a systematic solution to address demand volatility, thereby enhancing operational efficiency and competitiveness in the dynamic market landscape.

Keywords Incentive system · Asset administration shell · Capacity planning · Dynamic pricing · Forecast

1 Introduction

The global marketplace is subject to a multitude of influences, encompassing shifts in market trends, cultural dynamics, and uncertainties stemming from the legal and political landscape. These multifarious factors engender irregular demand patterns for service providers [1]. The repercussions of demand fluctuations on the operational efficiency of these providers are profound, yielding to sub-optimal resource utilization. This leads to increased costs [2], while delivery delays can result in penalties [3]. Shift, material requirements, and production process planning become increasingly complex due to large fluctuations in customer demand [4]. Service-oriented enterprises, unlike manufacturing firms, typically avoid maintaining inventories of finished goods due to the nature of their often non-storable products or services, with a focus on providing customized goods through a make-to-order approach or delivering services directly to the customer. Therefore, fluctuations in demand have an even more significant impact on capacity utilization for service providers [5]. For effective capacity improvement, companies must assess their maximum capacity and current planned utilization [6]. Consequently, service providers aspire to establish consistent demand profiles that facilitate optimal capacity utilization across their value chain. One strategic avenue to achieve this entails incentivizing customers to adapt their delivery schedules, thereby harmonizing demand with available capacity [7]. This approach holds particular promise for small and medium-sized enterprises (SMEs), which often grapple with more capacity limitations. Previous business processes between most SMEs, their suppliers, and customers were largely manual. Instead of integration and transparency, technical isolation and closed-mindedness prevailed. These circumstances often led to an unbalanced and unclear order situation, which in turn led to periods of overuse as well as periods of inefficient use of resources within the company.

To this end, a resistant and efficient framework is needed to facilitate the orchestration of these incentives and the alignment of customer demand with the prevailing capacity

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landscape. This paper addresses these challenges, by proposing a comprehensive system that integrates an incentive mechanism, capacity planning, and forecasting, which is connected by Asset Administration Shells (AAS) for a SME (cf. Fig. 1). The use of AAS provides a standardized framework for efficient data exchange [8].

The stated goal is to develop a tool that helps SMEs (Service Providers) to achieve a balanced order situation. The approach aims to optimize capacity utilization, strengthen operations, and improve customer loyalty while promoting sustainable resource use and technological innovation. To this end, forecasts (Forecast/Prognosis) are made for future customer orders, an incentive system for pricing is implemented, and a customer platform (Platform) is realized via which relevant information is shared with customers (Network Partner). The service provider and the customers form a production network in this context. AAS are used in the background to enable the exchange of information. The integration of potential digital services into process flows can be realized using new technologies. Existing assets, such as IT systems (Enterprise Resource Planning (ERP), Manufacturing Execution System (MES), Advances Planning System (APS), etc.) machines, and product data, need to be connected to enable such services. The proposed production system will offer customers reduced prices for the service provider's products when the predefined capacity is not fully utilized, compared to periods of full capacity utilization. For this purpose, an algorithm is implemented that takes the customer's order data (Order) as input data from the platform. In addition, the platform reminds the customer of their service and gives back an offer at the end. Via an interface to a capacity planning tool (APS), the algorithm receives the capacities in the period around the preferred date. Based on the order information and the capacities, the appropriate prices are calculated for the desired period. To ensure seamless integration within the company's structure, the process will be integrated and information will be shared with other systems. The AAS plays a crucial role in providing essential information related to the incentive system and capacity management.

In pursuit of the objective of developing a robust forecasting system, an incentive mechanism designed to harmonize customer demand, and the establishment of a customer platform, coupled with seamless integration into the organizational structure via the employment of AAS, necessitates a comprehensive exploration of various methodological approaches. To systematically address these multifaceted objectives, the structure of this paper is partitioned into four distinct sections. Section 2 discusses relevant related work. Each of these facets is subjected to evaluation, where diverse methodologies and strategies are assessed against pre-established criteria. This results in a research gap, which will be closed with the own approach in Sect. 3. In Sect. 4 the system is subjected to examination and validation. To exemplify the practical applicability of the developed system, a specific SME is selected as a case study. Section 5 concludes with a summary and an outlook for further research.

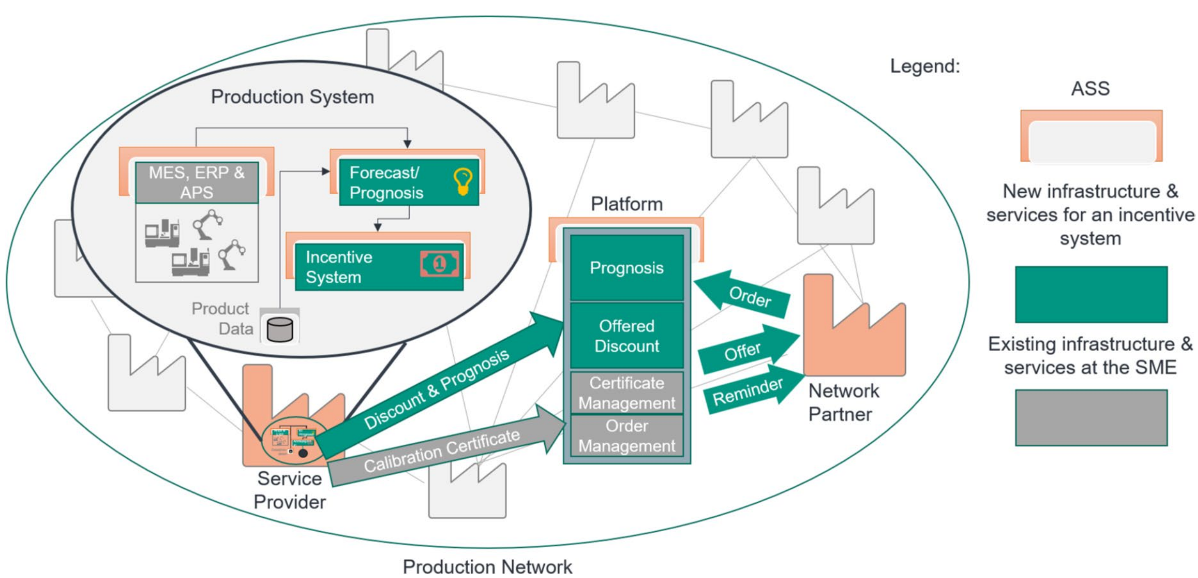

Fig. 1 Approach to smooth out fluctuations in demand by using an incentive system, forecast tool, capacity planning and AAS

2 Related work

This examination will be structured into four segments, each delving into a fundamental component of the proposed system: the Incentive System (Sect. 2.1), Capacity Planning (Sect. 2.2), Order Forecast (Sect. 2.3), and AAS (Sect. 2.4).

2.1 Incentive system

The following section evaluates different approaches that implement an incentive system. Each approach is evaluated in terms of the use of a dynamic pricing model, alignment with the company's current capacity, impact on demand balancing fluctuations, suitability for the B2B market, and applicability for service providers.

The approaches within this category can be classified into two distinct groups. The first group focuses on reactive pricing [9], which is based on the current measurement of capacity utilization [10], while the second group adopts an approach that adjusts prices based on stochastic prediction [11] and dynamic pricing [12]. The development and optimization of price functions across these approaches typically revolve around revenue maximization [13]. Although the optimal utilization of capacity and the smoothing of order fluctuations are among the intended outcomes, they are not the primary focal points of these incentive systems [14]. The price functions of the different approaches differ in that they have different dependencies. For example, the price depends on the level of the collateral stock [15] or the customer base is differentiated [16] and the price depends on the type of customer [17]. However, all concepts use a continuous price function. Staircase functions or different intervals that differ in price are not considered. Most of the methods were developed for B2B companies. Only approaches that aim to optimize a supply chain provide an incentive for companies through dynamic pricing [18]. Reinforcement learning and simulation models are used to balance demand during peak times [19]. The willingness to collaborate and the resulting horizontal cooperation, supported by transparency can lead to mutual benefits between suppliers [20]. Different sharing protocols can be used for dynamic partnerships where dynamic-distributed perform equally or better than centralized protocols [21]. This can be called coopetition where different network partners cooperate while they simultaneously compete with each other [22]. Coopetition can than help to support capacity investment decisions while information is collected between the partners [23]. Collaboration and dynamic pricing is also used to reduce non-conforming products and scrap rates [24]. Nevertheless, collaboration between SMEs still faces various barriers [25] but can mitigate the bullwhip effect, provide stability and enhance customer service [26]. From the perspective of sectors in which these incentives are predominantly employed, the retail industry takes the lead, while the development of incentive systems tailored specifically for service providers remains relatively scarce within the existing literature.

2.2 Capacity planning

To determine prices in the incentive system, the available capacity at the desired processing time needs to be calculated. The evaluation of existing approaches in the literature hinges on several key criteria: the integration of scheduling mechanisms, a comprehensive analysis of individual process steps, and the identification of bottlenecks within the production process. Furthermore, these approaches are analyzed to discern whether they engage in capacity planning that encompasses both present and predictive order volumes.

Typically capacity planning focuses achieving operational goals like avoiding capacity bottlenecks and only assesses remaining capacity implicitly. Either capacity planning is performed to minimize costs [27] and avoid penalties [28], or optimal production planning is performed to make the best use of production capacity [29]. If capacity planning tools have the goal of optimal capacity utilization and optimal production planning, production planning often analyzes each station in the production process individually. The total capacity of the production line is then an interaction of the individual capacities of the separate processes [30]. However, it is remarkable that the capacity is often determined for the entire production process. Hardly any approach focuses on the bottleneck of a production chain [31] or the integration of capacity planning and production scheduling [32]. Still, most of the capacity planning approaches developed are based on historical order data [33], resource states [34] and production utilization rates [35]. Only a few methods use a forecast of demand to calculate the future capacity [28].

2.3 Order forecast

To ensure the accuracy of projections regarding future capacity utilization, it becomes imperative to possess a dependable forecast about forthcoming orders. This task is accomplished through the application of a dedicated forecasting tool. The assessment of these approaches pivots on several critical aspects, including the intricacies of their forecasting algorithms, the nature of the foundational data they rely upon, and the overarching objectives guiding their predictive models.

To make a forecast of the demand on which an incentive system is based, different approaches of regressions, for example quantile regression [36] or censored regression [37], ARIMA models [38], machine learning [39] or stochastic approaches [33] are mainly used in the literature. It should be noted that most approaches are based on predicting customer demand and there are a few models that predict an optimal price at a given demand. The regression models are usually the simplest approach and require the least data pre-processing. In contrast, neural network models use multiple features to predict future demand, such as attributes about the product [40] or the point of sale [41]. All forecasting models have one thing in common, they require a large database when applied to different use cases to achieve representative results.

2.4 Asset administration shell

To connect the components discussed in the previous sections and integrate them into a value-added network, SME-friendly standard is required. This standard needs to be adaptable and flexible when integrating the various components. Various tasks such as data storage, information sharing, and program execution are precisely what the AAS technology as a standard was developed for. Therefore, in the following, approaches are examined that utilize AAS. These approaches are assessed based on the functionality of AAS, whether it has been adopted as a standard, and its use in interconnecting various components. It is striking that there are few use cases in which an AAS was used [42]. Mainly, the structure and design of the AAS are presented and standards are described [43]. Furthermore, an outlook on possible use cases is given [44]. So far, there is no approach in which the AAS maps an entire production network and in addition, controls complex process flows. AAS are used in the literature to integrate Industry 4.0 standards to production lines [45]. Mainly ASS are used to store and manage data. It is noteworthy that most approaches have not implemented a service view of AAS. This aspect of AAS functionality is not yet widely used in the literature, and when it has been, it tends to appear in recent publications [44]. Rarely in the literature, several AAS are implemented which exchange data with each other [46]. Mainly stand-alone solutions have been developed that cannot be directly embedded in sub-framework structures [47].

2.5 Research gap

The existing literature reveals several research gaps and limitations, particularly noticeable among SMEs. Firstly, current approaches that seek to smooth out order fluctuations primarily rely on dynamically adjusting prices as an incentive system. However, none of these approaches explore alternative incentives, such as the provision of supplementary services. This highlights a significant gap in the development of more diversified and effective incentive systems tailored for service providers.

Furthermore, there is an absence of an established incentive system that considers a service provider's capacity situation and simultaneously offers specific incentives for customers to align their demand with the available capacity. Such a system could enhance the profitability of service providers while ensuring that customers' needs are efficiently and satisfactorily met.

In terms of capacity planning, most approaches are developed as stand-alone solutions and are not integrated into a comprehensive process flow or system. They predominantly focus on reducing company costs rather than determining current capacity. As a result, capacity planning tools are not commonly used as a basis for implementing dynamic pricing. These tools aim to optimize process flows without establishing current utilization rates, and thus, descriptions of current orders and predictions of future orders are rarely included.

Regarding forecasting, existing models are applied to data sets with constant demand. No approach currently uses volatile data sets without eliminating outliers or deviations from the data set before the forecast. Additionally, most forecasting approaches apply to demand data only, without considering other features that influence customer demand. In the service industry, however, customer characteristics play a significant role and should be integrated into forecasting models.

The literature review indicates that volatile order fluctuations are not considered in forecasting models for service providers. Most forecasting approaches rely on data sets with constant demand, overlooking the significance of volatile data sets and the impact of outliers on accurate demand prediction.

In conclusion, there are significant research gaps in the integration of end-to-end digital networking through an AAS, particularly in optimizing the entire production process rather than addressing specific bottlenecks. The goal of this paper is to create an incentive system that effectively manages order fluctuations by implementing a seamless digital network. This network will incorporate order intake, customer-specific pricing calculations, and capacity planning. By integrating these components, the aim is to develop a comprehensive system that maximizes resource utilization, improves customer satisfaction, and enhances operational efficiency.

3 Approach

In this chapter, an incentive system tailored for the effective management of order fluctuations is presented. The system comprises the interconnected components outlined in Sect. 2. These components are linked through multiple AAS, creating a versatile, integrated system aligned with the overarching objective. An overview and concept of the entire system which offers customers suitable incentives, can be seen in Fig. 2.

It not only illustrates the interfaces of individual components but also showcases the role of AASs, which execute algorithms and programs associated with each component while facilitating the transfer of necessary data as input parameters. Customers interact with a dedicated portal for order submission, eliminating manual registration and coordination efforts. They request a service and their preferred order date. Upon order placement, relevant data is seamlessly transferred to an order AAS, interfacing with the incentive system AAS to calculate dynamic pricing based on available capacity. The incentive system AAS, composed of a submodel equipped with an operator, executes an algorithm based on input data sourced from the order AAS. Real-time pricing integrates with capacity planning tools, enabling proactive scheduling aligned with demand fluctuations. The capacity planning tool, enriched by a forecasting tool predicting and scheduling future orders, acquires comprehensive information from the service provider's ERP system. An AAS designed for this purpose facilitates the exchange of information between the capacity planning tool and the forecasting algorithm. Calculated prices, considering factors such as capacity utilization and customer segments, are communicated back to the customer portal for selection. To effectively address demand fluctuations, the system computes prices not only for the requested date but also for a predefined interval around it. This encourages customers to consider adjusting their order date to align with periods of lower demand, benefiting from reduced prices. The calculated prices are communicated back to the customer portal, where customers can conveniently choose their preferred service date. This selection is then transferred through the order AAS to the service company. The service company, upon manual review and confirmation, dispatches an order confirmation to the customer. Simultaneously, the order AAS transfers the order to the capacity planning tool, which proceeds to schedule the order. In summary, these interconnected components play a vital role in achieving the overarching goal. The following sections will delve into more detailed aspects of the system.

3.1 Capacity planning

As expounded in the previous section, the determination of capacity stands as a foundational element in the computation of the dynamic price, thus constituting an important

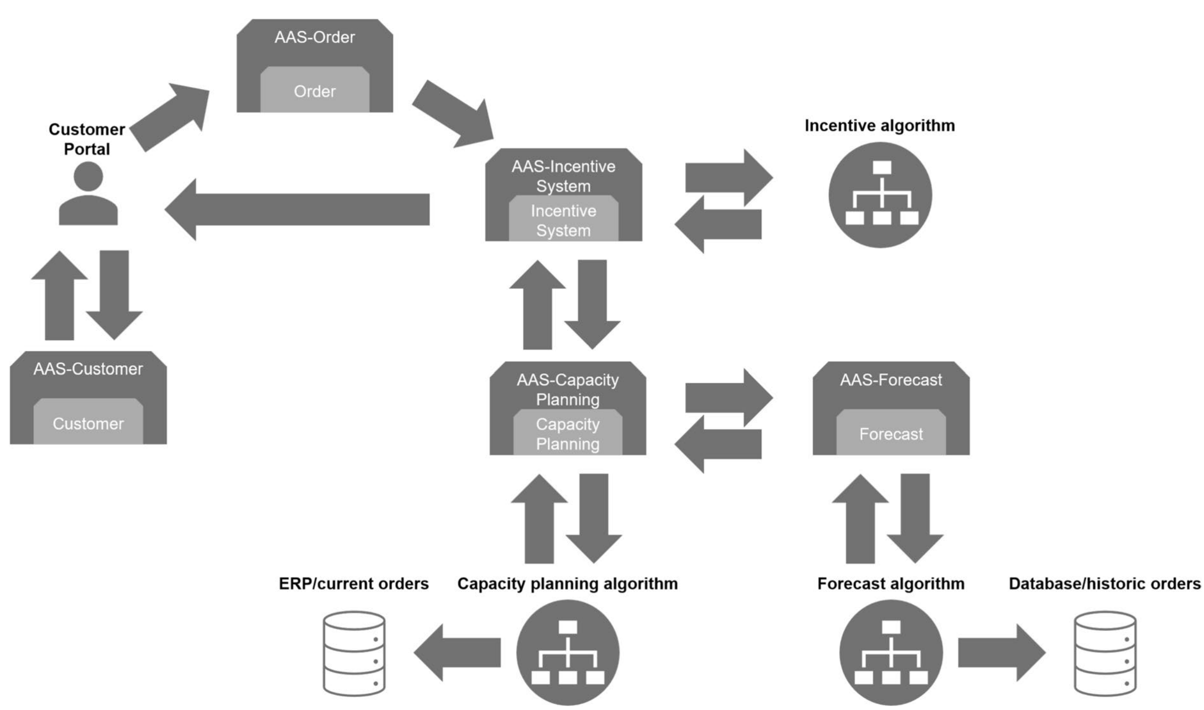

Fig. 2 Overview of the approach including algorithms and AAS

component within the overarching incentive system. Given that the pricing mechanism hinges on the accommodation of additional orders at a given point in time, the incentive system places particular emphasis on discerning the capacity of the current production bottleneck. The bottleneck serves as a judicious metric for gauging the potential acceptance of supplementary orders before reaching maximum capacity [48]. This strategic focus on the bottleneck simplifies the capacity calculation process, as the assessment needs to be conducted only for selected process steps rather than the entirety of the production process.

3.1.1 Identification of the Bottleneck

To be able to identify the bottleneck of the production flow, a value stream analysis is carried out [49]. The methodology aims to obtain a holistic view across the value chain [50]. The value stream shows the relationship between the flow of materials and the flow of information. The flow of information is becoming increasingly important here due to digitization [51]. The bottleneck in the value chain can now be determined from the holistic representation of the process.

3.1.2 Final capacity

In the process of determining an organization's capacity, it's crucial to first establish specific goals. These objectives can vary, such as maximizing the production of parts, ensuring efficient resource utilization, meeting customer demands, and maintaining high product quality. Following, the capacity assessment process is particularly relevant for SMEs [52], which often lack detailed information on process times. In such cases, process times need to be determined for a value stream analysis to accurately calculate capacity, which already was done in Sect. 3.1.1.

Once these process times are established, the next step is to define the availability of the workforce and operational resources. This involves considering long-term factors, such as different contracts and potential equipment defects. The outcome of this process is a clear understanding of the maximum capacities that are currently available. Subsequently, customer orders must be scheduled to align with these capacity constraints, with order information typically retrieved from the ERP system.

Given the variability in product specifications and the resulting differences in manufacturing processes for customer orders, it's necessary to break down these orders into distinct service bundles. For each bundle, a separate capacity calculation must be performed. Every service bundle within the orders must be scheduled based on the available capacity within a specific planning period. The level of detail of

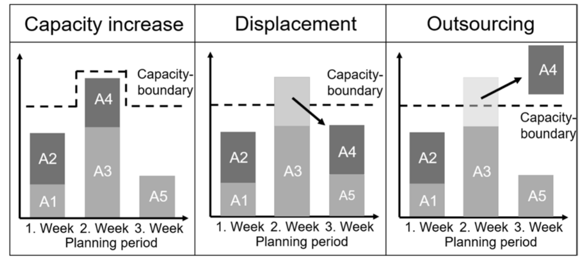

Fig. 3 Possibility of capacity adjustment according to Schuh and Stich [53]

this planning decreases with later planning periods. This capacity planning exercise is vital for identifying bottlenecks within the operational processes. Figure 3 shows the three strategies, increasing capacity, delaying tasks, or outsourcing, a company has when a bottleneck arises. However, it's essential to recognize that capacity increases are typically only feasible to a limited extent, as capacities are often inflexible and can only be altered in the medium to long term.

In the context of scheduling customer orders, it's important to align with the initially defined objectives. For those prioritizing customer satisfaction and timely service delivery, the First-In, First-Out (FIFO) rule should be applied, ensuring that customer orders are scheduled as early as possible. The primary objective remains to arrange orders in a manner that achieves a balanced utilization of capacity. However, volatile demand patterns can negatively impact this balanced utilization. Optimal planning of customer orders on available capacities can help address significant demand fluctuations. Nevertheless, this requires precise knowledge of future orders. Predictive models, based on historical data, can be employed to anticipate behavior. If it is feasible to forecast, based on the available data, when a customer is likely to use the service, capacity can be reserved for this purpose.

3.2 Forecast

As demonstrated in Chapter 2, making accurate predictions of orders is quite challenging, especially with a heterogeneous customer base and volatile order patterns. Nevertheless, it is crucial for mitigating order fluctuations to be able to predict future order timings as precisely as possible. With the help of a forecast, the future order situation can be best approximated based on past data [54]. In this approach, regression is used to forecast orders based on historical data. This method requires minimal data pre-processing and is effective even with smaller datasets. Using linear regression, it is possible to predict for each customer at which point in time the customer will use the service. Figure 4 illustrates that orders from an individual customer do not always arrive

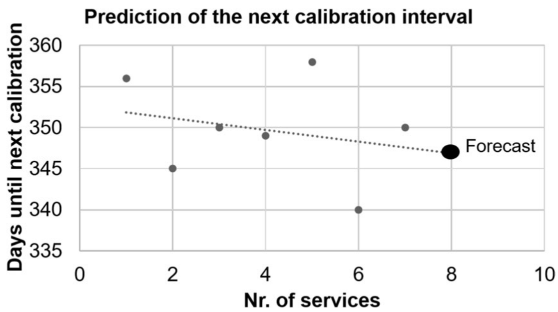

Fig. 4 Forecast of orders based on historic order data

at linear intervals and often exhibit outliers. However, linear regression effectively captures the entirety of the orders, creating a general overview of upcoming orders. This means that peculiarities or patterns in the order behavior of the entire customer base can be depicted using linear regression.

Regular recurring orders can therefore be taken into account in capacity planning. As a result, the predicted orders will also be considered in the price calculation for new orders and improve the balancing of demand fluctuations. The advantage is that the service provider can keep capacity free for the forecast orders. This makes it possible to realize a long-term even capacity load. The question arises whether the recurring sales order can be fully taken into account in capacity planning in a particular planning period since it is a forecast and it is only true to a certain probability. The capacity could be reserved at the wrong time. To spread the risk, forecast customer orders are therefore weighted using a normal distribution around the forecast order date. The normal distribution is best suited for probabilities [55]. In addition to purely historical forecasts, quality data is also incorporated. This allows the customer to receive not only a forecast but also a recommendation based on quality parameters. Accordingly, the projected date is adjusted, and a recommendation is provided to the customer, considering the quality data.

3.3 Incentive system

The following section describes the incentive system component. This component is responsible for processing order information with multiple products and determining a price based on various input data for the order. As depicted in Fig. 5, the incentive system AAS receives all information about the order through an interface with the order AAS and triggers the incentive algorithm service, providing all input data to the algorithm.

Since the price later depends on available capacity, the positions within an order must be arranged in a specific sequence. Because when calculating the price, more capacity is available than for the last product, the price of the last product in the order can be higher than that of the first product. Sorting the products based on their base price is a suitable approach for establishing the order. This involves arranging the products in descending order of their base prices, allowing the product with the highest price to receive the highest percentage discount. This method is advantageous as it is easy to implement and does not require significant computational time or capacity. Additionally, it enhances customer understanding and acceptance of this

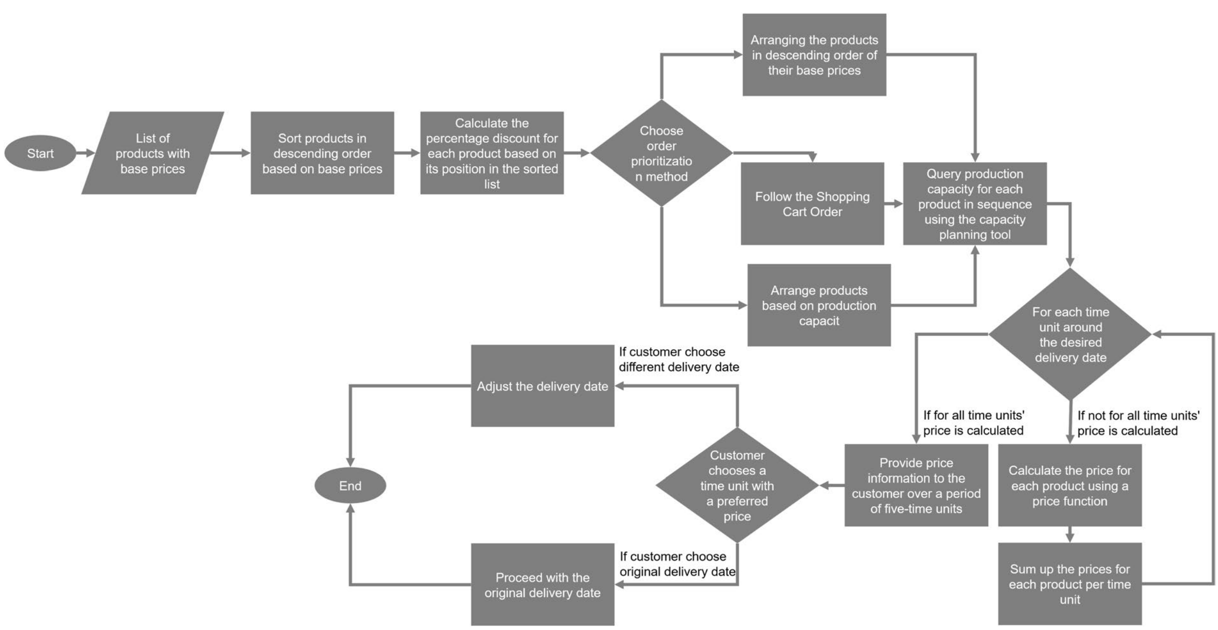

Fig. 5 Process of creating an incentive

step in the process. In this regard, different principles of order prioritization can also be applied to other SMEs. For instance, sorting products based on their required production capacity can be employed. Additionally, the order in which the customer adds products to the whole order can define the sequence for price calculation. The choice of these rules lies within the discretion of the SME, and in this approach, the base price is utilized as it is straightforward for customers to understand, leading to high customer acceptance. Once the order sequence is determined, the capacity for each product is queried in sequence using the capacity planning tool. The capacity is calculated for a time frame around the desired delivery date, such as two time units before and after the requested order date. For each time unit, the price for each product is determined using a price function, and the prices for each product are summed up per time unit. The customer is provided with price information throughout five time units. It can be assumed that customers tend to choose the lower price and may be willing to adjust their originally desired delivery date to benefit from a lower price.

Price function

As described in the previous chapter, the price of the service is calculated using a price function. The shape of the price function depends on the capacity and the selected product. There are various ways to represent a price function. In addition to a linear progression, or square root function, an exponential function can also be employed. Furthermore, the pricing function can be implemented as a step function. In a linear function, the price increase remains the same, regardless of whether the capacity increases from 10% to 15% or from 90% to 95%. However, it makes a significant difference for businesses whether they have low or nearly maximum capacity utilization. Hence, an exponential or square root function is advantageous because, with these functions, you can differentiate the price increase based on the capacity difference. The price function and its trajectory are contingent upon the product being offered and the composition of the customer base. In this approach, the price function is implemented as a step function, with the intervals determined based on the capacity utilization. This results in price tiers based on the level of capacity utilization.

A reason to use a step function is that the price does not immediately increase with a small change in capacity. This helps to prevent customers from feeling uncertain or confused when the price changes after reloading the web page, as it may be due to adjustments in capacity planning [56]. Additionally, the simplicity of the step function allows customers to easily understand and follow how the prices for their orders are determined, leading to higher acceptance of the incentive system. By using a step function, the price function offers clear and transparent pricing tiers that customers can comprehend, fostering a sense of fairness and encouraging their engagement with the incentive system [57].

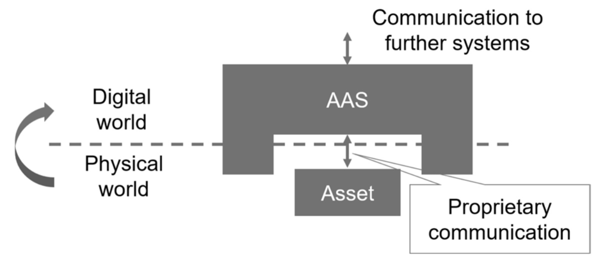

Fig. 6 Concept of an AAS

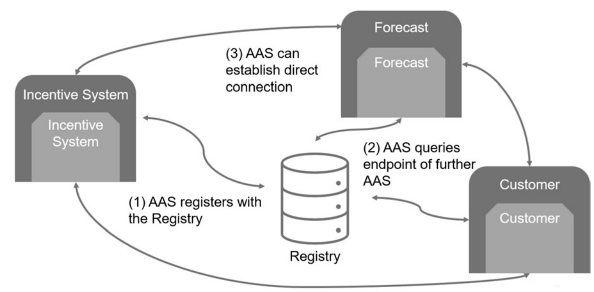

Fig. 7 AAS Registry based on [58]

3.4 Information exchange

To understand how information is exchanged between the individual components and how the algorithms of the components are executed by the AAS as a service, this section will provide a closer examination of the structure of the AASs. Figure 6 illustrates the concept of the AAS as a digital twin of an asset. Within a company, the AAS can store technical data and additional information such as operating costs or deadlines in sub-models.

The AAS is utilized for information exchange between different components in this approach. AAS provide access to all relevant customer information, including address, contact person, or historical orders which are saved in structured submodels in a database. By utilizing standardized interfaces, this information can be effectively transmitted to the respective components. One advantage of employing an AAS is the selective dissemination of required information to specific components, such as a customer portal. This approach optimizes computational resources and reduces the amount of data exchanged. Furthermore, the AAS is leveraged as a service in this approach. It includes an operator triggering an algorithm residing on a separate server, which can be initiated through an AAS interface. The algorithm receives input data via the AAS and subsequently returns output data to the AAS. The AAS needs to register themselves with a registry before they can interact (Fig. 7). Afterwards, other AAS in the registry can request the endpoints of the respective AAS. Then, the AAS can either access the service or obtain information from the requested AAS. [58]

4 Use case

4.1 Use case description

The customer data for the validation of the presented approach comes from a german calibration service provider. The company is a family-run specialist for the production and calibration of high-precision weights. Regular calibration of the measuring equipment is required to ensure its quality. The company's customer base is very heterogeneous and includes various industries. Many customers are manufacturers of scales or from the pharmaceutical sector. In addition, intermediaries of precision weights also order calibrations. Customers differ in their ordering behavior with regard to order volume, order frequency, order timing, and special requests. Therefore, the order situation is difficult to predict and fluctuates. The adoption of the outlined approach holds substantial appeal for this SME. The reason is that orders received via phone or email require manual handling before processing. Furthermore, the SME encounters seasonality, with a significant surge in orders, especially in the lead-up to and during the summer vacation season, resulting in capacity constraints.

4.2 Process overview

Figure 8 shows the final process of calibrating a weight set ordered through the customer portal through which the customer accesses their weight sets. Based on the forecast, the portal displays which weight set will soon require a new calibration from the service provider. Customers can select these weight sets and request a price quote. The information stored in the customer portal is passed to the incentive system. The incentive system calculates the corresponding prices and returns them to the customer. The customer selects a suitable calibration date which must be approved by the service provider. Approximately one week before the calibration date, the customer sends the weights to be calibrated. These weights arrive at the service provider and are calibrated and sent back to the customer within one week.

In the following, the process of price calculation and the structure of the individual AAS are discussed in more detail. After customers have selected their weight set to be calibrated, all information stored in the customer menu is transferred to the incentive system via an AAS. In addition to customer-specific data such as customer ID and calibration date, technical information on the weight sets is also stored. The customer data is stored in a submodel, the weight set data in a submodel collection. Figure 9 illustrates the structural composition of the order ASS. It comprises two components: a submodel containing all general customer information for those who have placed a calibration order with the SME, and a second part referred to as a submodel collection. Within this collection, all technical data related to the calibration weight sets provided by the customer is stored. Notably, each weight set possesses its dedicated collection.

In this example, the customer with the reference "2023-KND-56789" has requested the calibration of their set of weights on December 5th, 2022. The weight set consists of nine distinct weights classified as E1, and they are of the button weight type. Additionally, the weight set is uniquely identified by the ID “WS2023-9876”.

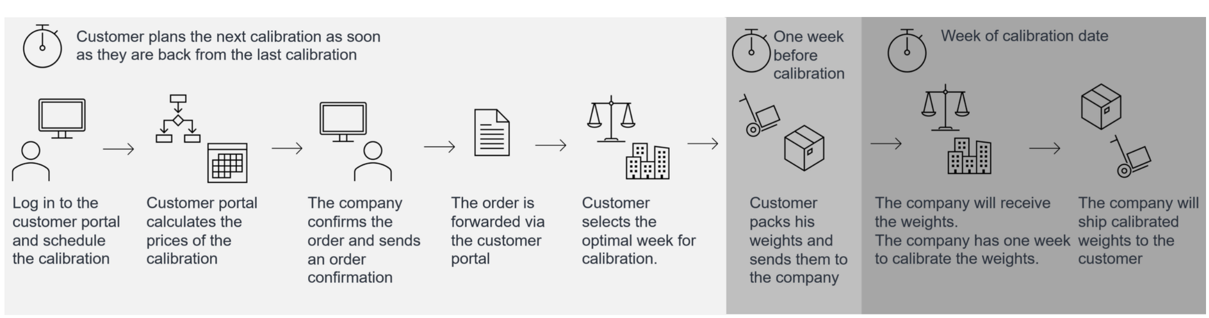

Fig. 8 Process overview: weight set calibration

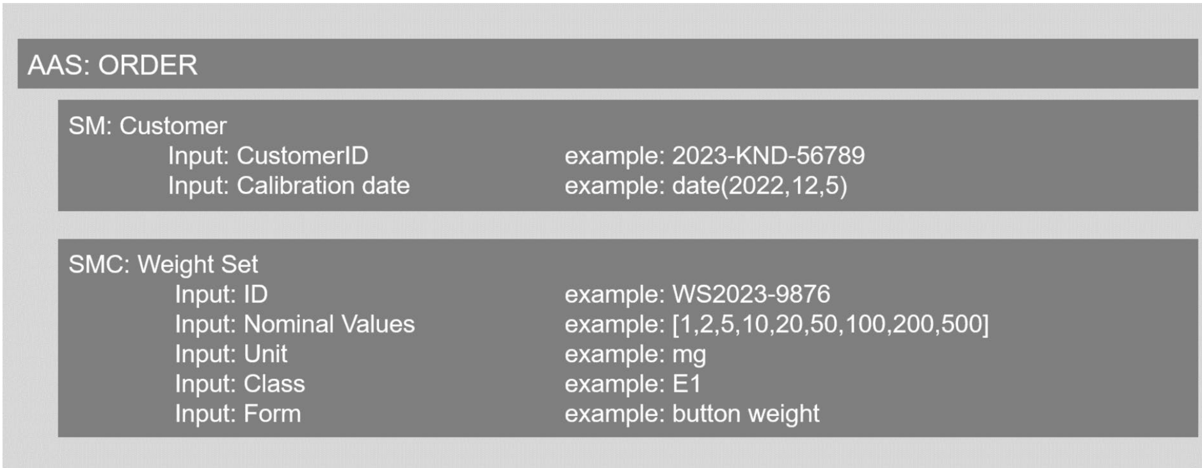

Fig. 9 AAS: customer order

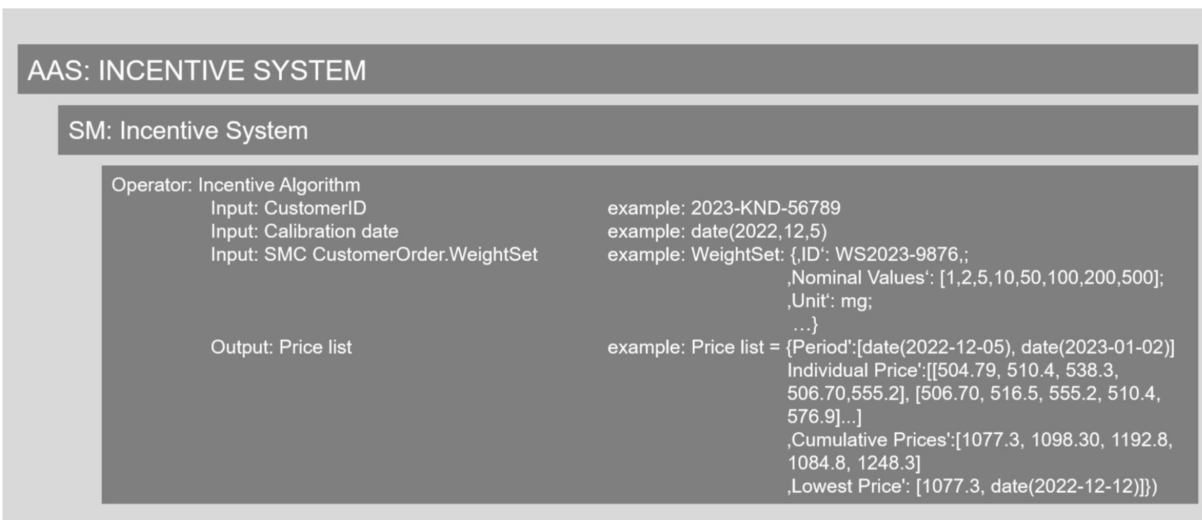

Fig. 10 AAS: incentive system

The actual algorithm that calculates the customer incentive is executed by an operator within the incentive system AAS. This operator receives input data from the order AAS, including customer data and information about the weight sets. Figure 10 illustrates the structure of the AAS and all input data relevant to the service of the incentive system.

The information about the sample customer "2023-KND-56789" is transmitted as described to the incentive system AAS. For the sample weight set "WS2023-9876," prices are calculated for an interval before and after the specified calibration date. In this example, this interval spans two weeks prior and two weeks following the calibration date. To simplify the calculations, it is assumed that each week exhibits uniform utilization of the calibration laboratories, resulting in a single price for the calibration of weight sets per week. In this case, the calibration laboratory utilization is highest in the fifth week, making calibration correspondingly more expensive. In contrast, in this example, the utilization is lower in the first week, leading to a lower calibration price. Should the sample customer wish to have multiple weight sets calibrated, a collective price for all calibrations per week is calculated based on the sum of the individual prices for each weight set.

The incentive algorithm, as described in section 3.3 assigns the weight sets accordingly and queries the available capacities for each weight set from the capacity AAS through the capacity planning tool. The capacity planning tool calculates the available capacities based on the already scheduled orders and the forecast. The incentive system

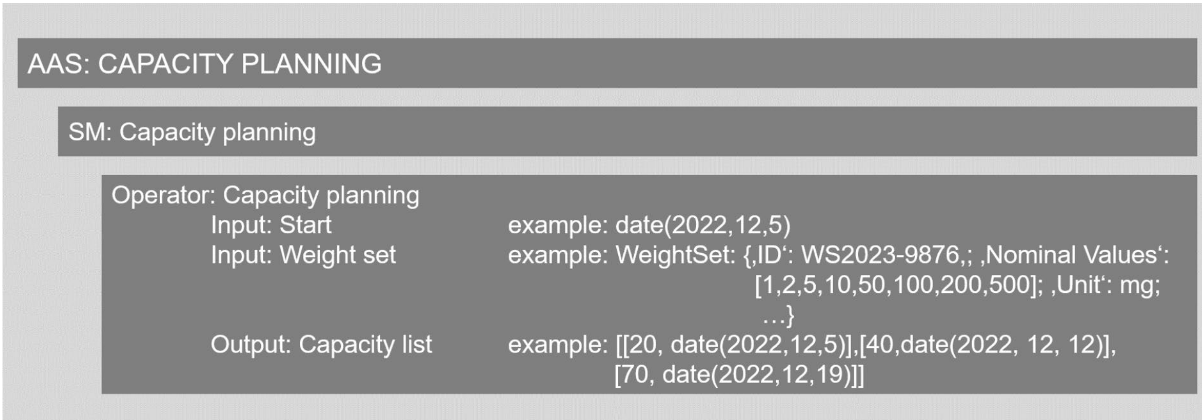

Fig. 11 AAS: capacity planning

receives information on the various available capacities for five weeks through the AAS. Similar to the incentive system AAS, the AAS depicted in Fig. 11 also consists of an operator. This operator possesses access to the capacity planning system and is responsible for transmitting all input data while receiving the output data from the capacity planning tool. The sample record is passed to capacity planning, which includes it in its plan and provides the occupied capacity for this weight record as output. This process is performed for all five weeks specified in the previously calculated time interval for price determination. As can already be seen in the prices, as shown in Fig. 10, it can be seen that the utilization is lowest in the first week and highest in the fifth week with the utilization of 70%.

The capacity planning tool also can query the forecast for orders through an AAS. This process is enabled by the operator, who triggers the service forecast. As illustrated in Fig. 12 two dates are provided to the forecast algorithm, delineating the forecasting period. In return, the capacity for each week is generated and delivered.

To use not only historical data for the prediction of future orders in this example, the forecast AAS transmits the time interval for which it returns the predicted number of orders. In this way, it can be seen that especially in the 5th week many orders are predicted.

Based on the available capacities for each weight set, the price for each weight set and week is calculated using the price function. Ultimately, the prices of the individual weight sets are summed up per week. The most cost-effective week is then determined. The prices, along with their corresponding week dates, are transmitted to the customer portal through the incentive system AAS. This allows the customer to view the prices in a calendar format for five weeks and make decisions based on their preferences.

The entire system, as implemented for the SME, is depicted in Fig. 13 The customer initiates their orders through the customer portal, where recalibration suggestions are presented. All necessary data for this process is stored in a database. The forecast AAS is utilized to communicate a laboratory recommendation to the customer, specifying when the weight set should undergo recalibration. In the background, the forecasting algorithm is activated, calculating the laboratory recommendation based on historical customer data,

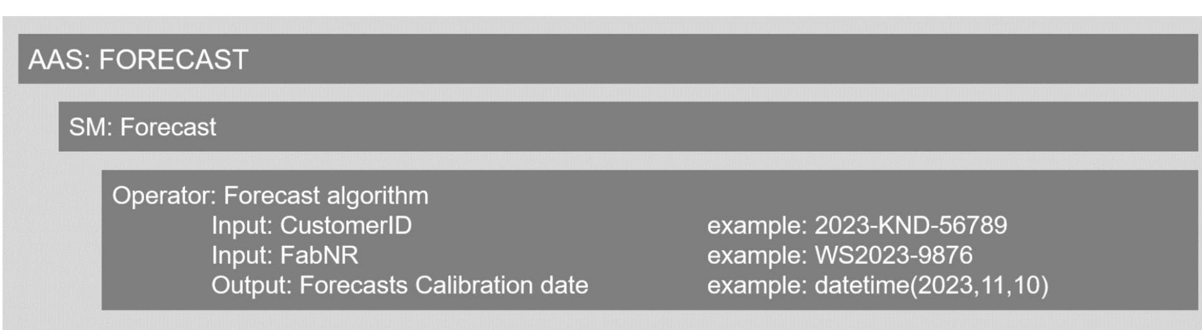

Fig. 12 AAS: forecast

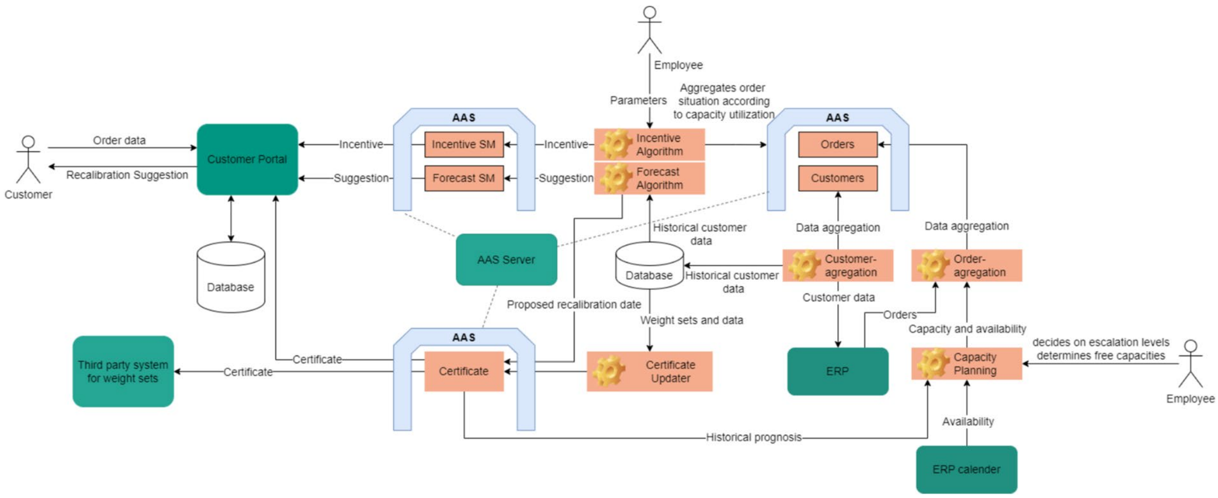

Fig. 13 Overview and AAS interaction in SME use case

considering both temporal and quality-related information. These data are also stored in a database.

In the second step, an incentive is computed based on the customer's selected date. This incentive aims to guide the customer according to the current capacity utilization. The confirmed orders from the customer are then stored in a customer AAS, linked with the ERP system. This establishes an interface with capacity planning, where new customer orders are scheduled, providing real-time capacity utilization for the incentive algorithm. As an additional service, the customer portal offers a digital calibration certificate, allowing access to the most up-to-date calibration values.

5 Conclusion and outlook

The objective of this approach is to develop a tool that enables SMEs in the service sector to achieve a balanced order situation, thereby allowing them to optimize their resource utilization. Additionally, it aims to integrate potential digital services into their operational processes. For this purpose, an approach has been developed through which a network can be established that addresses the challenge of fluctuating demand by implementing a program structure that enables the provision of individual incentives to each customer. This program structure includes an algorithm for calculating the incentives, a capacity planning tool that serves as the basis for the incentives, and a forecast algorithm for predicting upcoming orders. To facilitate seamless information exchange and service provision, several AAS have been implemented. By leveraging these tools and techniques, businesses can effectively respond to demand fluctuations and improve customer satisfaction.

This approach aims to improve the understanding of incentive systems in real-world scenarios. Following this work, all functional blocks and interfaces need to be implemented in a real-life environment. This implementation will provide a practical testing ground for the system. It is essential to involve real customers in these trials to assess their acceptance and gather valuable feedback. Furthermore, an important aspect to investigate is whether customers are willing to adjust their order deadlines in exchange for a larger discount. This analysis will help determine the effectiveness of incentives to customers with flexible delivery options. Additionally, the system has the potential for further expansion. By clustering the existing customer base, it is possible to create homogeneous groups of customers with similar characteristics. This clustering approach enables the development of customized price functions for each customer group, allowing for the provision of even more tailored incentives to individual customers. Further research should investigate the effects of deadline adjustments on customer behavior. Furthermore, it will explore the utilization of customer clustering to tailor personalized incentives with potential extensions to explore the scalability of the approach across different industry sectors and geographical regions, as well as the integration of machine learning algorithms to continuously optimize incentive strategies based on evolving customer preferences and market dynamics.

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Data availability The data sets generated during the study are not publicly available because they have not been released by the application partner.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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