

## Research Article

# Optimization of Supplier Development under Market Dynamics

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Over the last decades, supplier development has become an increasingly important concept to remain competitive in today's markets. Therefore, manufacturers invest resources in their suppliers to increase their abilities and, ultimately, to reduce their product prices. Thereby, most approaches found in the literature focus on long-term supplier development programs. Nevertheless, today's volatile and dynamic markets require flexible approaches to deal with this complexity. We apply Model Predictive Control to optimize the number of supplier development projects in order to achieve flexibility while maintaining a certain level of security for all parties. Thereby, the article focusses on a multimanufacturer scenario, where two manufacturers aim to develop the same supplier. These manufacturers can establish different levels of horizontal collaboration. While previous results already show the benefits of applying this approach to a static scenario, this article extends this formulation by introducing market dynamics in the numerical simulations as well as into the optimization approach. Thus, the article proposes to derive regression models using real-world data. The article evaluates the effects of real-world market dynamics on two use cases: an automotive use case and a use case from the mobile phone sector. The results show that assuming market dynamics during the optimization leads to increased or at least close-to-equal revenues across the involved partners. The average increase ranges from approximately 1% to 5% depending on the type and magnitude of the dynamics. Thereby, the results differ depending on the selected collaboration scheme. While a full-cooperative collaboration scheme benefits the least from regarding dynamics in the optimization, it results in the highest overall revenue across all partners.

## 1. Introduction

Rapid development and advancement of technologies lead to frequent product changes and short production life cycles [1]. As a result, companies are concentrating on core competencies and outsource activities to other companies and service providers [2]. Thus, the number of supply chain members increases, and then, companies consider collaborating closely to stay competitive in their markets [3]. Moreover, the increasingly globalized market becomes ever more dynamic, influenced by massive demographic and socioeconomic shifts [4]. Dynamic markets are characterized by frequent and uncertain changes in product preferences and customer demands, in product and production technologies, and the competitive landscape [5]. These

market turbulences increase the ambiguity and risk in companies' business processes, requiring a stronger collaboration between the involved companies and their respective business strategies [4]. Collaboration becomes increasingly significant, as no company can individually be competitive and provide the spectrum of products and services to satisfy today's customer demands. Consequently, collaboration has become a core trading mechanism [6]. Moreover, the increasing technological specialization of products and a stronger focus of companies on their core competencies lead to a requirement for highly specialized components. For the procurement of such components, supply chain partners tend to form mid- to long-term relationships [7]. Component and material costs often amount to over 50% of a product's manufacturing price. For this

reason, researchers and practitioners have shown an increasing interest in so-called supplier development programs in the last decades [8].

Research on this topic has shown that extended programs increase the reliability of such relationships, while short-term contracts provide higher flexibility, in particular in turbulent markets. Therefore, companies may be reluctant to engage in long-term agreements, which possibly reduce their tendency to invest in supplier development activities [9]. To establish a trade-off between the benefits of short-term and long-term contracting, several researchers proposed the application of a receding horizon technique [10–12]. This approach derives a long-term plan for supplier development activities but only applies a part of it in each step. Their applied approach has the potential to estimate the overall duration of the planned supplier development program but, at the same time, supports a frequent reevaluation and adaptation. They only focused on a monopolistic constellation of a single manufacturer and a single supplier. Nevertheless, in real market situations, manufacturers often tend to obtain components from the same supplier. This involvement allows suppliers to participate in several supplier development programs, which might influence each other and, thus, introduce hardly predictable dynamics to the effectiveness of each supplier development program. Consequently, Dastyar and Pannek extended the approach of this study to a multimanufacturer scenario, utilizing different game-theoretic collaboration schemes [13]. Nevertheless, while this allows handling the dynamics introduced to the supplier development program by competitors, it does not allow planning under market dynamics. As mentioned before, current markets tend to be increasingly turbulent, which also influences the effectiveness of supplier development programs, e.g., by price fluctuations, both for the manufacturers' products and the production costs or by sudden changes due to a frequent introduction of new product generations.

Consequently, this article aims to extend the approach by enabling an integration of market dynamics into the mathematical model. The primary objective is to evaluate how market dynamics influence the overall benefits of different settings of collaboration between manufacturers. Therefore, the remainder of this paper is structured as follows. Section 2 presents the state of the art for supplier development and introduces the baseline models. Section 3 renders a summary of the collaboration schemes mentioned above. Afterward, real-world data from the telecommunications and automotive industry in Germany is analyzed to establish generalized models of the market dynamics for two distinct products. Subsequently, the article presents the adaptation and implementation of these models and a numerical study of their effects on the profit of supplier development. Finally, the article ends up with a discussion of the obtained results.

## 2. Literature Review

In the current literature, several authors deal with the topics of supply chain collaboration and supplier development.

Nevertheless, only a few approaches combine both aspects. This section presents a summary of related previous studies below.

*2.1. Collaboration in Supply Chain.* Today is the age of adaptive and intelligent supply chains, which is a new generation of networks and communications across the different partners to deal with dynamics, such as supplier failures or demand uncertainty [14]. Engaged companies in the supply chain are more concentrated on their local objectives rather than on the performance of the whole chain. Therefore, centralized management approaches, where a single partner such as the logistic center optimizes the global performance, are becoming less realistic and are being replaced by decentralized management approaches [15]. In a decentralized management approach, each member optimizes its performance, while communication with other partners can improve the individual and global performance [15]. Researchers differentiate between different possible settings, such as coordination, cooperation, and collaboration. These terms have become popular to define the strategy that companies within a supply chain employ to approach their external partners [16].

Looking back on nature [17] and the economics of companies [18], the setting of transactions have shifted from market transactions to authorized transactions. However, because of economic, environmental, and social pressures, the level of production factors' integration increased. Consequently, transactions have evolved from open-market negotiations to coordination, cooperation, and finally to collaboration, as shown in Figure 1.

The first phase, *open-market negotiations*, focused on short-term relationships based on a minimal amount of information sharing. The phase of the open-market negotiations was followed by the phases of *coordination* and *cooperation*. Coordination refers to a designed and orderly alignment of partners' actions to achieve common goals, and cooperation refers to a joint effort to achieve a determined goal with a clear understanding of contributions and benefits [19]. Unlike the preceding two phases, a recent evolutionary phase (*collaboration*) not only has taken various forms, including the supply chain collaboration and collaborative logistics, but also extended and virtual enterprises [19, 20]. Kozar differentiates between cooperation and collaboration [21]. She emphasizes that, under cooperation, partners can perform their assigned responsibilities separately and bring their results to the table. While, under the collaboration, partners are involved in close interaction with each other to achieve common goals, thereby negotiating and accommodating others' perspectives [19, 21].

In supply chain collaboration, partners collaborate to share information, logistics facilities, and resources to improve cost efficiency without compromising service levels. Supply chain collaborations categorize as vertical, horizontal, or lateral, according to the collaboration scope [22]. The vertical collaboration aims to integrate one supply chain consisting of suppliers, manufacturers, retailers, and customers. Horizontal collaboration occurs among logistics

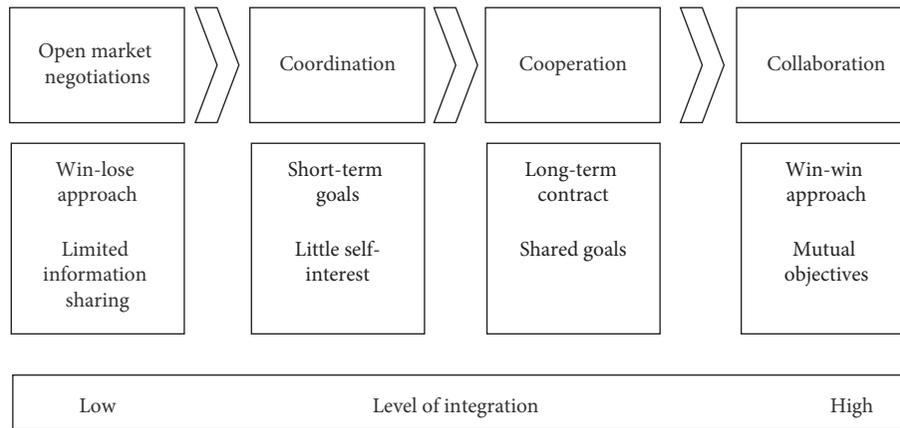


FIGURE 1: Supply chain interaction formation [19].

actors at the same level of the supply chain, for example, collaboration among suppliers or manufacturers. Lateral collaboration is a combination of the two latter approaches [19, 23, 24].

Following this classification, this study focuses on lateral collaboration in terms of supplier development. In particular, it focuses on the horizontal collaboration between manufacturers in combination with vertical supplier development programs.

**2.2. Supplier Development.** To compete effectively in the world market, a company must have a network of competent suppliers. Supplier development enables companies to create and maintain such a network and improve various capabilities of their suppliers to deal with increasing competitive challenges [25]. As manufacturing companies focus on their core competencies, greater reliance is being placed on suppliers to design, develop, and deliver innovative, cost-competitive components, and subassemblies. Researchers have identified the need for supplier improvements in many areas, including quality, delivery, cost reduction, and new technology adoption [26].

Supplier development generally defined as “any effort by a buying firm to improve a supplier’s performance and capabilities to meet the manufacturing firm’s short-term and/or long-term supply needs” [27]. According to this definition, manufacturing companies typically initiate, design, and administrate supplier development activities. Noshad and Awasthi presented a review of supplier development in academic literature and practice [28]. In this study, they highlight that, in 2013, almost 70% of manufacturers across the automotive, aerospace, and electronics industry applied supplier development.

Supplier development aims to increase a partner’s capabilities or performance, e.g., in terms of responsiveness, product or service quality, reliability, or generally in terms of cost [29]. Therefore, it provides a valuable tool to establish strategic and competitive advantages for the entire supply chain [30]. The literature presents four main classes of supplier development strategies: supplier relationship management, supplier reward programs, training, and

implementation support, and finally, the commitment of resources (e.g., [28]). As can be seen from this list, supplier development always requires investments from the manufacturer into its supplier and often involves the transfer of expertise between both partners.

Over the last decades, supplier development received increasing attention in research and practice as a new concept. Most literature focusses on qualitative concepts, such as the use of certain operations in the supplier development context [31], or essential success elements [32]. As an instance, Krause states that supplier development programs are more effective if manufacturers’ conduct relationship-specific investments. Moreover, when partners expect the continuation of the relationship, the tendency of companies to participate in supplier development activities is higher [27]. According to Dyer and Singh, adequate protection mechanisms might affect both dealing costs and inclination of companies to invest relationship-specific resources in supplier development. In the first case, companies achieve an advantage by incurring fewer transaction costs to achieve a defined level of supplier development specificities. In the second case, companies create relational rents. These rents are possible when partners combine, exchange, or invest in specific assets, while they employ effective governance mechanisms with lower transaction costs [33]. Such mechanisms become increasingly important when several manufacturers incur in relationships with the same supplier. Examples for such situations can be found, e.g., for electric motors in washing machines (Whirlpool and GE), engines in automobiles (Toyota and Pontiac), and PC boards in personal computers (Dell and HP) [8]. In such cases, secure legal contracts are applied to increase the security of all parties [31].

Apart from these basic concepts of supplier development, several studies focused on the investigation of practical applications in various industries, e.g., [8, 13, 16, 34, 35]. According to these studies, Toyota started preparing on-site support to engage suppliers in the Toyota Production System [34]. Boeing, Chrysler, Daimler, Dell, Ford, General Motors, Honda, Nissan, Siemens, and Volkswagen followed this collaborative procedure to develop suppliers’ performance or capabilities in order to deal with increasing competitive challenges [35].

In terms of quantitative evaluations of supplier development, some authors proposed models to evaluate the efficiency of supplier development programs. Bai and Sarkis applied various game-theoretic models, to reveal how profits of supplier development investments are affected by multiple relationships among manufacturers and suppliers. The results illustrate that a cooperative relationship is more economically beneficial to the supply chain. However, it requires more capital resources and knowledge investments than a noncooperative relationship [16]. Talluri et al. developed two scenarios: a scenario consisting of a single manufacturer and multiple suppliers and a scenario consisting of two manufacturers and multiple suppliers. They investigated the supplier development problem from a long-term investment perspective. In their two-manufacturer scenario, they assume that, through cooperation, a manufacturing company can enjoy the benefit of the other company's investment, whereas in a noncooperative situation, a manufacturing company benefits only from its own investment. Similarly, the two cooperative manufacturers will face the same level of shared risk [8].

Dastyar and Pannek provided a set of optimization models to address the risk of supplier development [13]. They considered a centralized and a distributed setting with two manufacturers and a supplier. By imposing Model Predictive Control, they attempted to simulate and minimize the risk of future investments of manufacturers. They implemented cooperative and noncooperative scenarios to assess the impact of these scenarios on manufacturers' revenue. They concluded that the cooperative setting between manufacturers paid off better than noncooperative and collaborative settings in longer investment horizons. However, for shorter investment horizons, the noncooperative setting performs better than the rest. Due to shorter periods of supplier investment, the manufacturers and the suppliers gain flexibility, and this flexibility is advantageous for the manufacturer and the supplier [13].

Meanwhile, the presented models investigate the efficiency of supplier development in various constellations, and they generally assume fixed market conditions and neglect the influence of market dynamics. Since decision makers should be aware of the gained profit of their investment in supplier based on the dynamic market situation, the ever-changing markets' conditions have to be taken into account. To tackle the mentioned issue, we applied two use cases to study the profitability of the supplier development investment for manufacturers implementing real-world data. Section 3, therefore, shortly summarizes a model for the dynamic extension of supplier development contracts as well as its extension to several game-theoretic modes of collaboration between the involved manufacturers. This model provides the baseline to evaluate the efficiency of supplier development programs under market dynamics.

### 3. Methodology

This article builds upon the model presented in [11] and the collaboration modes offered in [13]. We use Model Predictive Control (MPC), which is capable of establishing

optimal control under high dynamics [36]. See, for example, Grüne and Pannek for details about this control scheme as well, for example, applications [37]. The application of mathematical models in general and of control theory is increasing in decision-making in supply chain management [11–13, 38]. The MPC itself is a well-established simulation strategy to deal with uncertainties in supply chains, see, e.g., [39].

**3.1. Model Predictive Control Scheme.** The MPC scheme combines short-term closed-loop control of the real-world system with a model-based, long-term open-loop optimization, as shown in Figure 2. The open-loop simulation provides an optimized sequence of activities (controls  $u$ ) based on the simulation of the real-world system. The algorithm then applies the first part of this sequence and measures the state of the real-world system  $x$  at predefined sampling steps  $t_{mi}$  with a sampling horizon of  $T$ . MPC obtains a new optimal sequence for each consecutive measurement. As a result, it can provide long-term predictions of activities, while frequently reevaluating these sequences, reacting to unforeseen changes in the real world. This behavior is particularly suitable to estimate the efficiency of supplier development programs in non-monopolistic scenarios and for turbulent markets. On the one hand, turbulent markets are hard to model, and changes may occur unpredictably. On the other hand, manufacturers may have to deal with uncertain or incomplete information in multimanager scenarios, depending on the chosen collaboration scheme.

The proposed algorithm relies on three different components: First, the system model, which describes the state of the real-world system. MPC's open loop uses the system model to simulate the effects of controls. Second, to derive optimal solutions given a specific system state, the optimizer uses a cost function. Finally, the proposed approach uses one of the four collaboration schemes, which determine the order of decision-making, and the information available for each manufacturer in each time instance  $t$  is applied.

**3.2. Collaboration Schemes.** Dastyar and Pannek propose four collaboration schemes, each differing in the sequence of decision-making and the manufacturers' system models. These schemes describe different information available to each manufacturer during decision-making [13]. For making the decisions, the optimizer uses the cost function  $J$  given in equation (1). Thereby, the fully cooperative scheme constitutes the only exception. This scheme applies the sum of both manufacturers' cost functions for the optimization:

$$J = - \frac{(a - c_m - c_s \cdot x(t)^m)^2 - r^2}{4b} - c_{sd} \cdot u(t). \quad (1)$$

In this equation,  $a > 0$  represents the customer's willingness-to-pay, denoting the price a manufacturer can achieve for its product on the market. Moreover,  $c_m > 0$  and  $c_s > 0$  indicate the production costs for the manufacturer and the supplier, respectively. The suppliers manufacturing cost

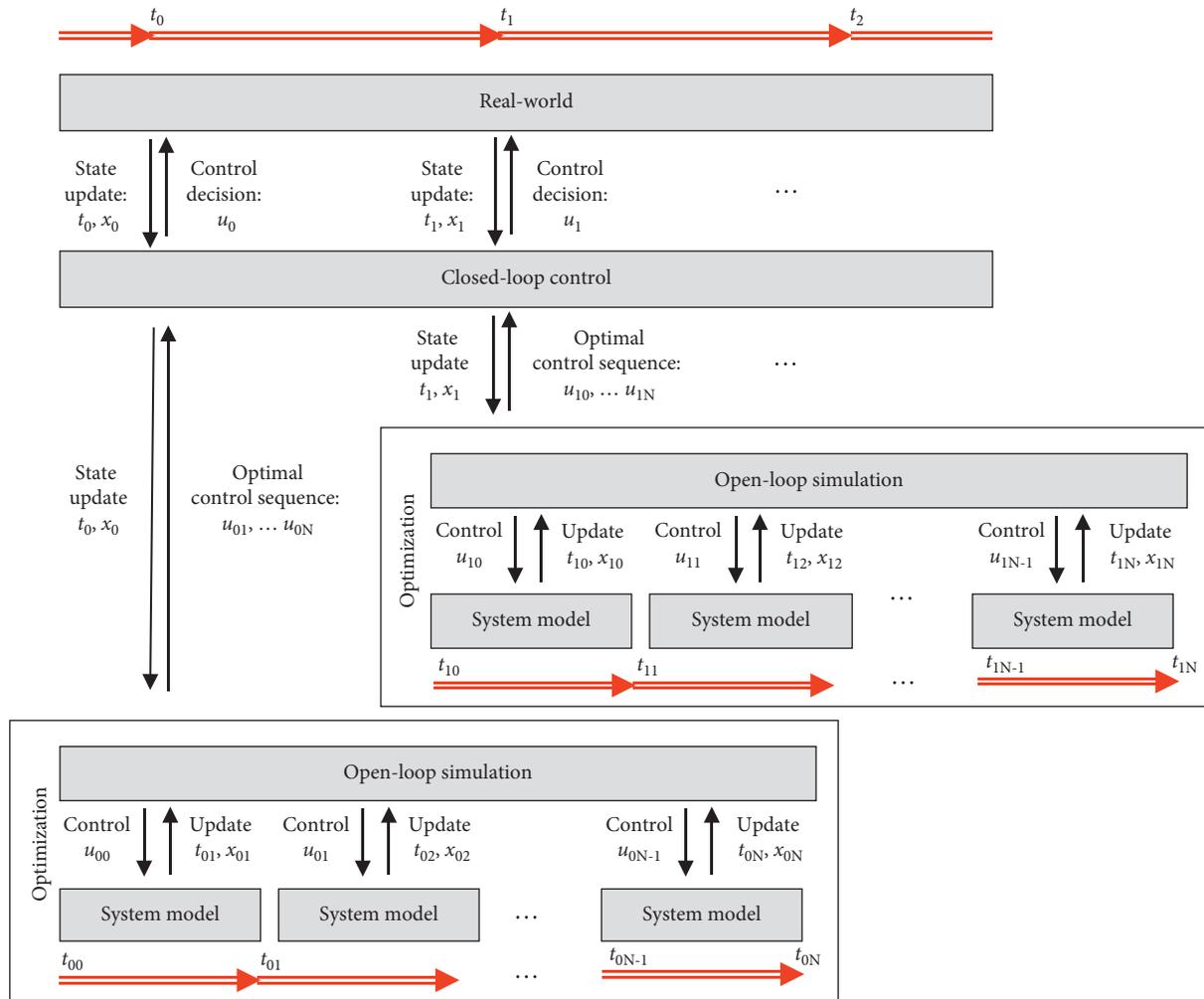


FIGURE 2: MPC control scheme [13].

is multiplied with  $x(t)^m$  to describe the effects of supplier development programs. Thereby,  $x(t)$  represents the current system state at time instance  $t$  and  $m < 0$  is the respective supplier's learning rate. As a result, an increasing system state leads to reduced production costs for the supplier. The parameter  $r > 0$  represents the supplier's fixed revenue per product. Finally, the parameter  $b > 0$  denotes the price elasticity, describing how much the price of a product changes if the demand fluctuates. The second term of the cost function represents the manufacturers' investment in supplier development programs. Therefore, the cost for a supplier development activity  $c_{sd} > 0$  is multiplied with the current control value  $u(t)$  at time instance  $t$ . This control value describes how many projects or activities are funded by the respective manufacturer at the given time instance. Each of these projects increases the state  $x$  by one, effectively reducing the suppliers manufacturing price. Please refer to [11, 13] for a more detailed derivation of this cost function.

The collaboration schemes differ primarily in the order of decision-making and in the system model, which the open-loop optimization applies to simulate the effects of controls. In contrast, the closed-loop system model always records all supplier development projects conducted by all

manufacturers to initialize a new open-loop iteration. Figure 3 schematically depicts the four collaboration schemes, including the order of decision-making (red and blue squares) and the information exchange (black arrows) between the manufacturers. It is to mention that these decision-making processes repeat at each sampling step of the simulated planning horizon during the open-loop optimization.

For the *fully cooperative* scheme, both manufacturers make a joint decision. As mentioned earlier, this mode optimizes over the sum of both manufacturers' cost functions. Therefore, both manufacturers are fully aware of the other one's investments and try to achieve the best strategy of maximizing the profit across both partners. The system model for both manufacturers is given by  $x(t) = x(t-1) + u_1(t) + u_2(t)$  with  $u_i$  denoting the current control for manufacturer  $i$ . The optimizer optimizes  $J = J_1 + J_2$  concerning  $u_1$  and  $u_2$ .

In the *noncooperative* scheme, the complete opposite holds. Every manufacturer makes decision on its own, not being aware of the other manufacturer's investment in the same supplier. Therefore, the system models are given as  $x_i(t) = x_i(t-1) + u_i(t)$  with  $i$  denoting the index of the

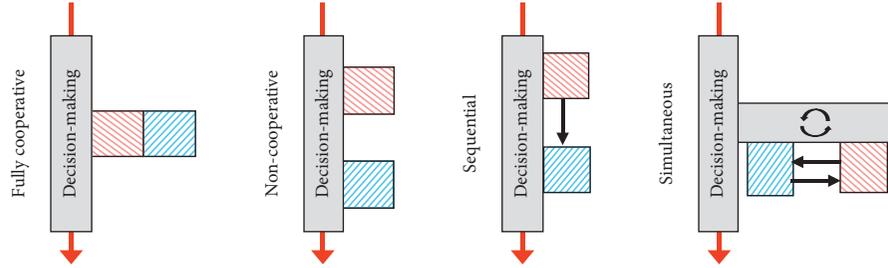


FIGURE 3: Order of decision-making and information exchanges based on different collaboration schemes.

manufacturer. Respectively, this scheme conducts two separate optimizations, each optimizing  $J_i$  concerning  $u_i$ .

The *sequential* and *simultaneous* scenarios represent a mixture of the abovementioned scenarios. The manufacturers perform distinct optimizations, trying to achieve the maximum profit for themselves. Therefore, they access different levels of information about the other manufacturer's investment plans.

The *sequential* scenario assumes that one manufacturer makes its decision independently and informs the second manufacturer about its plans. The second manufacturer then renders its decision using this information. Therefore, the system models are given as  $x_1(t) = x_1(t-1) + u_1(t)$  and  $x_2(t) = x_2(t-1) + u_1(t) + u_2(t)$ . As with the noncooperative scheme, manufacturers conduct two distinct optimizations, each optimizing  $J_i$  concerning  $u_i$ .

Finally, the *simultaneous* scheme assumes that both manufacturers render their decisions separately, but both provide their decisions to the other one. This behavior represents a negotiation between both partners. Therefore, the system models are given as  $x(t) = x(t-1) + u_1(t) + u_2(t)$  and the optimizer minimizes the respective  $J_i$  with respect to  $u_i$  only. To imitate the behavior of negotiating, decision-making occurs cyclically. Both manufacturers render their decision, communicate it to the other, and, using this new information, make a new decision. This iteration is performed either until there are no changes in the manufacturers' plans or until it reaches a certain iteration limit.

The presented model and its derivative collaboration scheme provide a useful tool to optimize supplier development programs. Nevertheless, besides other actors, i.e., additional manufacturers, changes in the current market situation impose additional dynamics, which cannot be handled by these models. Consequently, Section 4 presents an extended formulation, which modifies the cost function in equation (1) to rely on additional models of these market dynamics. Furthermore, the section presents two exemplary use cases, using real-world data, to demonstrate how these additional models could be obtained. The reformulation aims to enable more realistic assumptions during the open-loop optimization for all of the previously proposed collaboration schemes.

#### 4. Cost Model and Market Dynamics

Extending the cost function provided in Section 3, we include market dynamics by assuming that some of the

described parameters can change with each new time instance. This modification mainly refers to the willingness-to-pay ( $a$ ) and the production costs of the manufacturer ( $c_m$ ) and the supplier ( $c_s$ ). This section first introduces the use cases analyzed in this article and provides a short overview of incurring costs, which attribute to the market dynamics. Afterward, this section describes the modification of the cost function and the derivation of the corresponding models for  $a$ ,  $c_m$ , and  $c_s$ .

**4.1. Scenarios for Market Dynamics.** In this study, we select two types of products to investigate the effect of price dynamics on the revenue gained by supplier development. We assume Samsung smartphones' market as a short life-cycle (high-technology) product and Mercedes-Benz A-class cars as a middle life-cycle product, as these markets show very distinct characteristics.

A large number of manufacturing technology-based industries have evolved at an impressive speed, showing rapid transitions in terms of both product features and manufacturers' competitive dynamics. The mobile phone industry is one of the most prominent examples. The global mobile phone industry has faced radical changes since its birth [40]. Rapidly changing market dynamics, such as increasing market penetration, intense global competition, and the need to respond rapidly to changes in technology, rapidly shrinking product life cycles, and mass-consumer preferences have continuously shaped the industry over time. Over the last two decades, the fast introduction of new product technologies and the propensity for the demand of products with rich and even unrelated features have transformed the mobile phone into a multifunctional device [41]. Mobile phones, as many high-technology products, subject to short product life cycles, short life on the market, a steep decline stage, and the lack of a maturity stage. Thereby, the short product life cycle relates mostly to the length of time the product spends on the market [42].

Similarly, many researchers studied the automotive life cycle [43]. As an instance, Cao et al. investigated the product life-cycle management in the automotive industry using RFID. They proposed cars' life cycle in three stages: beginning-of-life (BOL), middle-of-life (MOL), and end-of-life (EOL). Beginning-of-life is the stage of the product's design and manufacturing. The middle-of-life phase starts when the product has emerged, purchased by the customer, or used and repaired when it is necessary. The final phase, end-of-

life, refers to the stage when the customer has completed their use of the product and releases it for decommissioning [43]. As the present study focuses on the product life cycle in the market, we only consider the MOL stage of the cars' and mobile phones' life cycles (producing cars and selling to the market). Based on the MOL stage, cars represent a middle life-cycle product, while mobile phones represent a short life-cycle product.

To compare the market situation for mobile phones and automobiles, they have different life cycles and very different market dynamics. The market price of mobile phones generally declines significantly after the new model releases to the market. This condition is not valid for automobile market prices. In the car market, the prices change slowly when a new model presents to the market. Moreover, car prices remain comparably stationary when compared to the high dynamics of mobile phone prices.

**4.2. Derivation of Models for Market Dynamics.** This section first presents current drivers of market dynamics by analyzing the structure of incurring costs for each company. Afterward, it describes the modifications required to include market dynamics into the proposed approach.

Variable manufacturing costs divide into three broad categories: direct materials costs, direct labor costs, and manufacturing overhead [44]. Given the cost function in equation (1) and the descriptions provided above, the cost function contains three terms, which should be adapted to include market dynamics: the customers' willingness-to-pay ( $a$ ), the production costs of the manufacturer ( $c_m$ ), and the supplier ( $c_s$ ). We consider these parameters as time dependent, to represent gradual changes in these values over time, resulting in an adapted cost function  $J$  as follows:

$$J = -\frac{(a(t) - c_m(t) - c_s(t) \cdot x(t)^m)^2 - r^2}{4b} - c_{sd} \cdot u(t). \quad (2)$$

As a result, only the supplier's revenue ( $r$ ), the cost for supplier development projects ( $c_{sd}$ ), and the price elasticity ( $b$ ) remain static. The effects of the learning rate ( $m$ ), as an exponent to the time-dependent system state, already shows dynamic characteristics over the current system state in the original cost function.

**4.3. Source Data Used to Derive the Market Dynamics.** We analyzed data corresponding to the described use cases and derived generalized regression models to simulate realistic market dynamics. The datasets for the *production costs* come from the database of Germany's Federal Office for Statistics [45] for both use cases. The selected datasets contain monthly values over the last ten years as of 2018. Therefore, we used several time series relating to the "production of cars and car engines", "production of parts and accessories for cars", "production of devices and installations for telecommunications," and "production of electronic components and circuit boards" to derive appropriate models for the use cases' production costs. The

following sections provide a more detailed description of the used source data.

For the *willingness-to-pay*, we analyzed the development of prices for products chosen over different time horizons. For the mobile phone market, we collected the prices of the cheapest phone model of the Samsung S-Series and for the product generations S5 to S9 from various price comparison sites across the Internet. The mean value for each day was calculated to serve as the dataset for the price development of mobile phones. Thereby, we did not consider currency exchange rates in this averaging. The derived models only aim to characterize the general market dynamics without focusing on a particular currency. As a result, we obtained a time series for one model in five generations. For the automotive segment, we used the Mercedes-Benz A-Class as a sample product. To obtain the required time series, we used Mercedes' annual list prices for new A-Classes in Germany since its introduction until now. This time series covers three generations of cars. Thereby, each generation consisted of three baseline car models used in conjunction to obtain the generalized market dynamics in terms of the willingness-to-pay, i.e., the price development.

**4.4. Regression Models: Willingness-to-Pay.** We created two distinct models as part of each use case to obtain an estimation of market dynamics concerning the price development. The first model ( $a_{gen}$ ) generalizes the price development of all product generations; the second model ( $a_{init}$ ) generalizes the price development of all generations' initial prices. The parameter  $n$  denotes the average number of months a product model stays on the market until a new generation emerges. The parameter  $a_0$  denotes the initial price of the first model of the first generation introduced to the market. Consequently, the functions  $a_{init}$  and  $a_{gen}$  both are normalized to provide multipliers for this initial price. As before,  $t$  indicates the current sampling instance in months from  $t_0$ . The values  $t_g$  and  $t_{\Delta g}$  denote the last instance  $t_g \leq t$ , where the manufacturer launched a new product generation and the number of instances inside the current generation's life cycle as  $t_{\Delta g}$ . Accordingly,  $a(t)$  is defined as follows:

$$a(t) = a_0 \cdot a_{init}(t_g) \cdot a_{gen}(t_{\Delta g}) \quad \text{with} \quad (3)$$

$$t_g = \lfloor \frac{t}{n} \rfloor \cdot n; \quad t_{\Delta g} = t \bmod n.$$

We split the time series into two distinct datasets to characterize the functions  $a_{init}$  and  $a_{gen}$ . The first dataset, used for  $a_{init}$ , consists of the initial prices for newly introduced product generations. The second set, used for  $a_{gen}$ , consisted of the normalized prices of each model in each generation. Thereby, we normalized the prices by the corresponding models' initial price. We interpreted these different time series as repeated measurements of the same experiment, resulting in five measurements for the mobile phones (S5 to S9) and nine repeated measurements for the automotive use case (three generations with three models per each). Figure 4 depicts the corresponding plots of the measurements and the resulting regression function. Thereby, solid line depicts the predictions of the regression

function (mean estimation) for the displayed data points. The gray crosses depict the normalized source data. The figures labeled as “price development” depict the functions  $a_{gen}(t_{\Delta g})$ . As described, for the automotive use case, these correspond the annual list prices of the Mercedes A-Class for each generation, while the mobile phone use case provides the daily prices for each generation (S5 to S9) aggregated from several price comparison sites across the Internet. Thereby, we normalized each value by the generation’s initial price. The figures labeled “release price” show the normalized initial prices for each generation as crosses on the  $y$ -axis and the month of release on the  $x$ -axis. These again depict the regression function for  $a_{init}(t_g)$  as a solid red line. The figure for the automotive use case shows that all three models use the same coefficient for their new generation’s initial release price. The mobile phone use case only uses a single product model during this analysis.

Figure 5 displays the comparison between the obtained estimation for the willingness-to-pay with the recorded time series using a base price of 600€ for the mobile phone and 14,418€ for the automotive use case. The latter results from converting the price of the first A-Class from Deutsche Mark (DM) to Euro (€). The figure shows that the models reproduce the general trend for both use cases quite well. We selected the initial price for the automotive comparison corresponding to the midclass car model of each generation. Therefore, the estimation also follows this model in the middle of the measurements. Comparing the estimation to the price development of this model, we achieve a Pearson correlation coefficient of 0.973. According to Figure 5, some deviations between the estimation and the measurements exist in the mobile phone use case, resulting in an overall Pearson correlation of 0.837. Despite those slight differences, these models generalize the market dynamics quite well in terms of the product price efficiently.

**4.5. Production Cost  $c_m(t)$  and  $c_s(t)$ .** As described earlier, production costs generally split into material costs, labor costs, and overhead costs. For this study, we also include the energy cost as one of the primary factors; thus, consider it separately from the overhead. The cost functions given in equations (1) and (2) differentiate between the production costs of the manufacturer and the supplier. Moreover, as these cost functions include both the supplier’s production cost and revenue, we assume that these represent the manufactures’ direct material costs ( $(c_m t)$ ). We consider the production costs as given in equations (4) and (5). Similar to the formulation of the willingness-to-pay, both equations rely on initial values for  $c_{m_0}$  and  $c_{s_0}$ , while the dynamics are formulated as multipliers for these initial values:

$$c_m(t) = \alpha_2(c_{m_0} \cdot c_l(t)) + \alpha_3(c_{m_0} \cdot c_e(t)) + \alpha_4(c_{m_0}), \quad (4)$$

$$c_s(t) = \alpha_1(c_{s_0} \cdot c_{mat}(t)) + \alpha_2(c_{s_0} \cdot c_l(t)) + \alpha_3(c_{s_0} \cdot c_e(t)) + \alpha_4(c_{s_0}). \quad (5)$$

Thereby, vector  $\alpha$  denotes the proportion of the corresponding material costs ( $c_{mat}$ ), labor costs ( $c_l$ ), energy costs

( $c_e$ ), and overhead ( $c_o$ ). All of the parameters show time-dependent behavior over  $t$ , while the overhead is static. As for the willingness-to-pay, the models include the corresponding trends as normalized multipliers for a provided base cost to only represent the dynamics, independent from any actual momentary values.

We obtain the time series from the DE-STATIS database of Germany’s Federal Office for Statistics [45] to consider the corresponding dynamics. All of these time series covered ten years of monthly recordings from 2008 until 2018. DE-STATIS offers data for various industrial sectors. We apply the data of the following industry sectors to conform as close as possible to the selected use cases. For the automotive use case, we use the data of “production of cars and car engines” as the cost of the manufacturer and the data of “production of parts and accessories for cars” as the cost of the supplier. In the mobile phone use case, we apply the data of “production of devices and installations for telecommunications” as the cost of the manufacturers and “production of electronic components and circuit boards” as the cost of the supplier. Therefore, we apply the following time series (tables) from DE-STATIS to generate the corresponding regression models.

**4.5.1. Cost Structure for Producing Companies.** By aggregating the values provided in this table, we characterized vector  $\alpha$  as the average proportion of the corresponding cost category over the last ten years for each sector.

**4.5.2. Price Index for Energy.** Price indices provide the relative development of a specific value over the years. As a result, these relative values were used directly to obtain a regression model for the development of energy prices without further normalization and preprocessing. Moreover, we assumed that the dynamics in energy costs did not differ between the different sectors and used the same model in all calculations.

**4.5.3. Employees and Turnover of Enterprises in the Manufacturing Industry.** This table contains various information about the number of employees, turnovers, and labor costs for each sector. By dividing the amount of paid labor costs by the reported number of working hours, we calculated the monthly average wage in each industry sector. This value was again normalized by dividing through the initial value to achieve the multiplier required for equations (4) and (5). Finally, a regression was performed to obtain the time-dependent trend for each sector.

**4.5.4. Manufacturing Price Index.** Similar to the price index for energy, this time series represents the relative change in reported manufacturing costs for each sector. While these values can serve as a benchmark for the estimation of  $c_m(t)$  and  $c_s(t)$ , we can also use them to estimate the dynamics for the supplier’s material costs. Under the assumption, that this index comprises the four mentioned cost categories, we can use vector  $\alpha$  and the regression models for  $c_l$  and  $c_e$  and

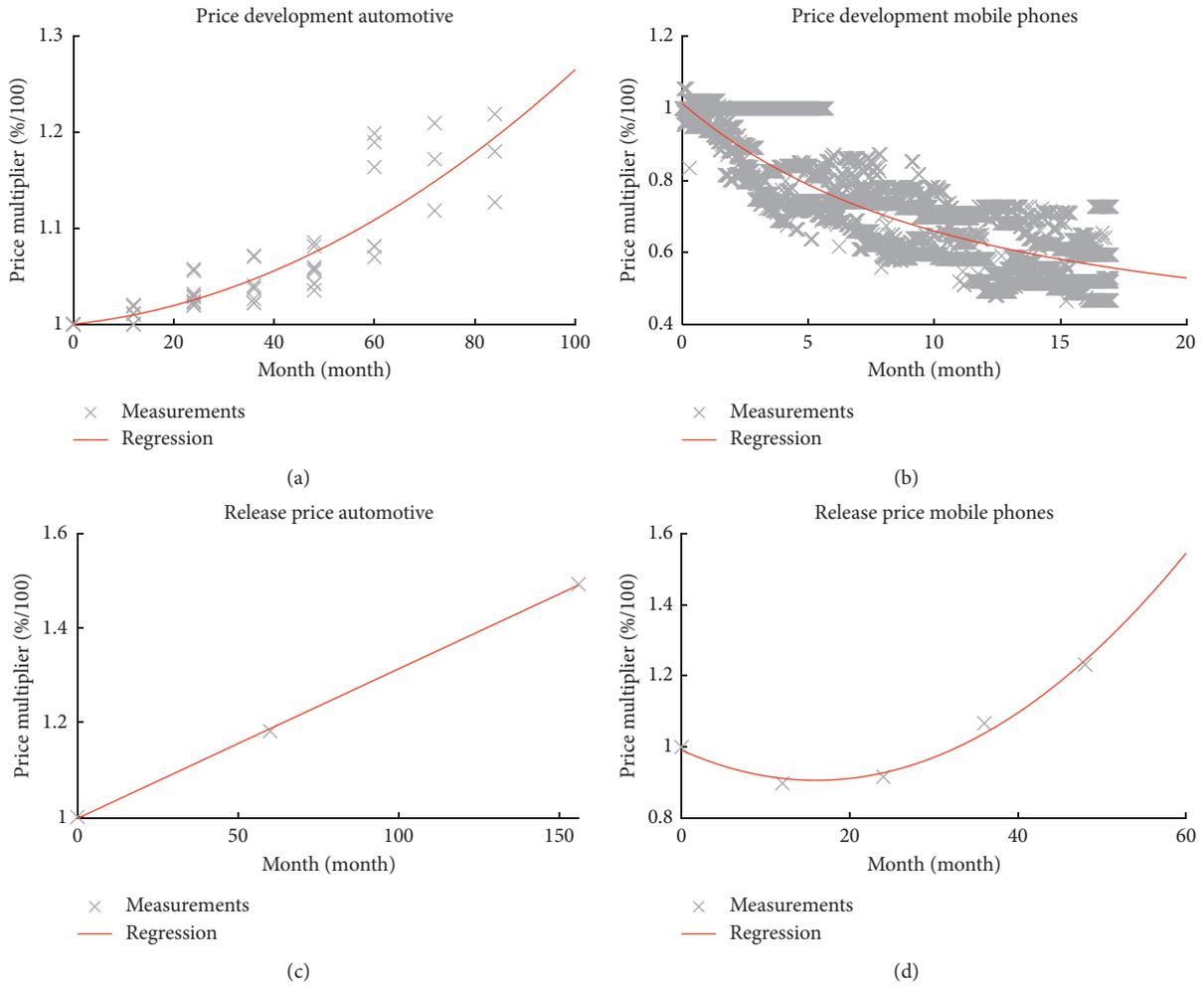
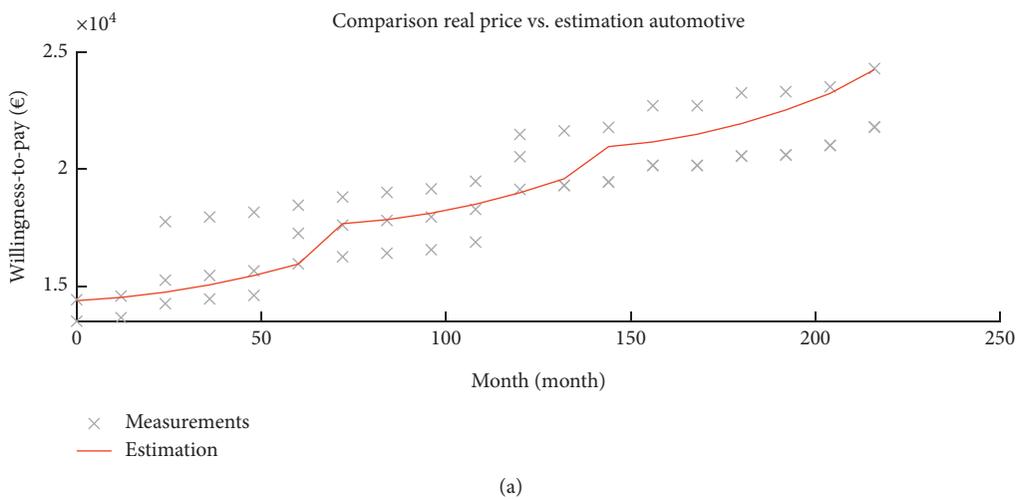


FIGURE 4: Regression models for release price ( $a_{init}$ ) and price multiplier ( $a_{gen}$ ) for automotive and mobile phone use cases.



(a)  
FIGURE 5: Continued.

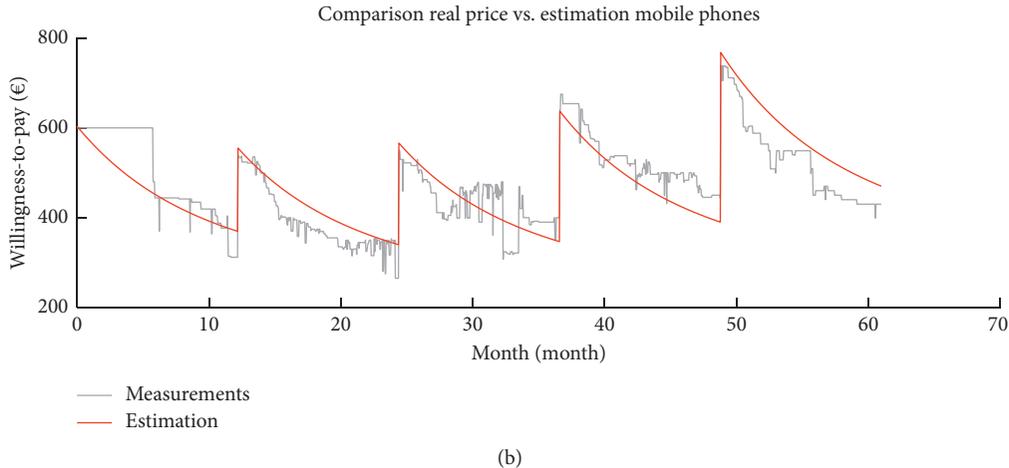


FIGURE 5: Comparison between the estimation of  $a(t)$  and the real-world historical data for willingness-to-pay.

attribute the remainder of the dynamics in the manufacturing price index to the material costs.

By combining these regression models, we estimate the production costs as given in equations (4) and (5). Figure 6 depicts the comparison between this estimation and the recorded historical data. As Figure 6 shows, the models provide an accurate representation of the observed real-world trends for all four industries. For this comparison, we define the base costs  $c_{m0}$  and  $c_{s0}$  as 1.0 to enable a direct comparison with their respective manufacturing price index.

## 5. Numerical Evaluation

This section presents the results for a set of numerical simulations. These simulations aim to evaluate the difference in the presented optimization approach with and without assuming market dynamics. Thereby, we optimize each use case twice: once we include the models described in the last section (equation (2)) into the open-loop prediction and once we assume static values for the variables  $a$ ,  $c_m$ , and  $c_s$ . The simulation scenarios follow the same structure as in the previous work (c.f. [13]). Section 5.1 describes the simulation scenarios. Section 5.2 first presents a comparison of the manufacturers' behaviors for both use cases, with and without dynamics. Finally, Section 5.3 evaluates the difference between static and dynamic assumptions in dynamic markets in terms of the total revenue of supplier development.

**5.1. Experimental Design.** Table 1 summarizes the parameters used in the simulation for both use cases. The simulations for the static and dynamic scenarios both use the same set of parameters as initial values. Thereby, the static scenarios use the provided values for  $a_0$ ,  $c_{m0}$ , and  $c_{s0}$  for each time instance, while the dynamic scenarios use the time-dependent regression functions described earlier. To setup the scenarios, we use the same basic structure provided in the previous work. Therefore, we assume two manufacturers, whereby one manufacturer shows stronger dependence on the supplier, given by a different distribution of the manufacturing cost  $c_{m0}$  and supply cost  $c_{s0}$ .

To calculate the parameters in the table, we first assume an arbitrary value for the customer's willingness-to-pay  $a_0$ . This value describes the amount of money a manufacturer will receive for its product. We assume that each manufacturer aims for revenue of 10%, which we subtract from  $a_0$ . Then, we select the manufacturers' production costs  $c_{m0}$  as either 50% (manufacturer one, M1) or 60% (manufacturer two, M2) of the remaining amount. The leftover amount distributes to the revenue  $r$  (10% of this amount) and production costs of the supplier  $c_{s0}$ . As a result, the first manufacturer shows a stronger dependence on its supplier. We assume that this manufacturer tends to invest more money into its supplier development program, resulting in higher values for  $c_{sd}$  and  $p$ . The maximum number of fundable projects per sampling step  $p$  and the price per project  $c_{sd}$  are adapted to match the higher values for  $a_0$  accordingly. Thereby, the second manufacturer's project prices  $c_{sd}$  only amount to approximately two-third of the prices for the first manufacturer. We keep the values for the price elasticity  $b$  and learning rate  $m$  comparable with previous works, as given in [13]. The use of such a cost distribution ensures that both experiments remain comparable, even if selecting different initial values for the product price (willingness-to-pay). By applying the same percentages to all other parameters, the experiments can assure that observed effects only result from the corresponding use-cases' market dynamics. Thereby, the percentages applied by this study have been chosen randomly and, in contrast to the market dynamics, do not follow any real-world use case. Nevertheless, practitioners can quickly adapt the optimization to their own needs by modifying the percentages above.

**5.2. Evaluation of the Manufacturers' Behavior under Static and Dynamic Assumptions.** Figures 7–10 depict the behavior of manufacturers for the automotive and mobile phone use cases. Thereby, Figures 7 and 8 show the behavior for the case, where the open-loop simulation does not assume market dynamics (static), while Figures 9 and 10 show the case of assuming market dynamics (dynamic). Each of these

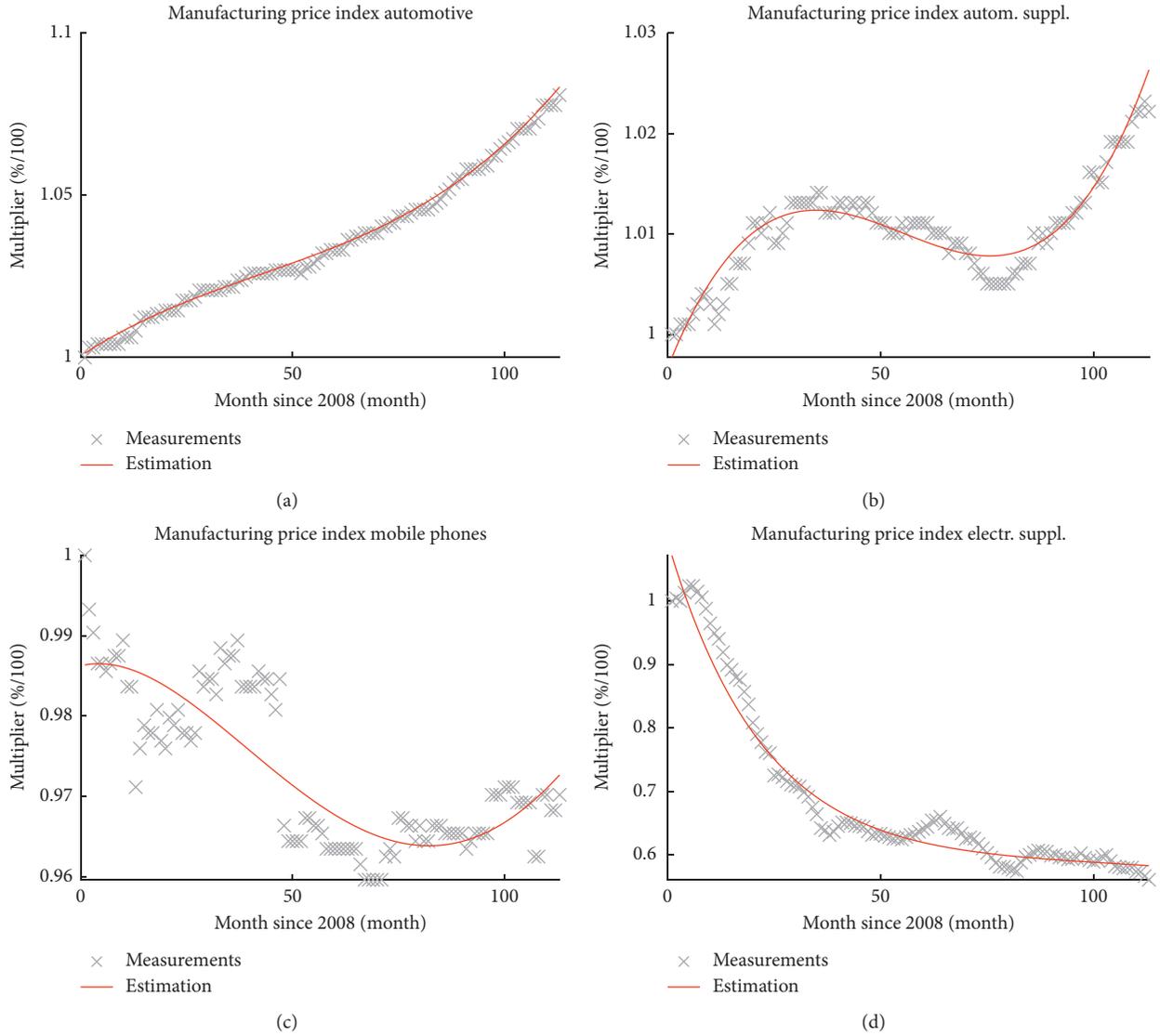


FIGURE 6: Comparison between the manufacturing price index obtained by Germany’s Federal Office of Statistics in each industry sector with the estimation calculated by equations (4) and (5).

TABLE 1: Experimental setup.

Param.	Description	Automotive		Mobile phones	
		M1	M2	M1	M2
$a_0$	Initial willingness-to-pay	10,000	10,000	500	500
$c_{sd}$	Cost for SD projects	3,000,000	2,000,000	13,000	9,000
$c_{m0}$	Initial prod. cost for manuf.	4,500	5,400	225	270
$c_{s0}$	Initial prod. cost for supplier	4,050	3,240	202.5	162
$b$	Price elasticity	0.01	0.01	0.01	0.01
$r$	Revenue of supplier	450	360	22.5	18
$m$	Learning rate	-0.1	-0.1	-0.1	-0.1
$p$	Maximum number of SD projects per period	20	10	10	5
—	Sampling horizon	6 months		1 month	
—	Open-loop horizon	54 months (4.5 years)		12 months	
—	Closed-loop horizon	240 months (20 years)		84 months (7 years)	

figures shows the number of projects funded by each manufacturer as a black or red line, and the values for  $a(t)$  and  $c_s(t)$  (gray) at each time instance. For the static assumption, the latter are gray, horizontal lines on top and at the bottom of the plot.

While in this study we applied real-world data, the results of the static scenarios show the same behavior as the results of Dastyar and Pannek [13]. In the beginning, both manufacturers invest in their supplier development program and cease investments after the projections show a high enough effect. Furthermore, investments after this point do not amortize within the open-loops prediction horizon. For the noncooperative scheme, both manufacturers cease their programs quite early, assuming no further revenue from the program. In the fully cooperative scheme, the results show an extended period of investments, resulting from the higher, combined revenue. Moreover, the figures show that especially manufacturer two invests for a prolonged period, as its investment prices are lower, but the effects are equal. The sequential and simultaneous schemes show different behavior for the automotive use case in Figure 7. Here, manufacturer two ceases investments right at the start and only relies on investments performed by manufacturer one; when manufacturer one ceases its program, manufacturer two picks it up and finishes it by investing until it expects no further increase in revenue. The sequential setting supports this opportunistic behavior, as manufacturer one invests anyways. The simultaneous scenario shows this behavior due to the asymmetrical dependence on the supplier. As the number of funded projects acts as a multiplier to the production cost of the supplier (c.f. equation (2)), the efficiency of each funded project directly depends on the supplier's production cost. All scenarios, given in Table 1, assume higher supplier costs for the first manufacturer. Consequently, this manufacturer also gains a higher benefit of each project and is more likely to invest.

The results and behaviors in Figure 8 follow the same logic for the mobile phone use case. Nevertheless, the generally lower parameter values result in shorter investment horizons across all collaboration schemes. The sequential and simultaneous scenarios, in particular, show a decreased time span for investments. Manufacturer two ceases its program very early and, contradictory to the automotive use case, does not pick it up again. This behavior shows that generally lower values result in shorter supplier development programs, i.e., that further investments become uneconomic faster if prices are low.

Both use cases show very different behaviors when the open-loop simulation assumes market dynamics, as shown in Figures 9 and 10. The automotive use cases (Figure 9) depicts a comparable behavior as the static use case in the beginning: manufacturers both begin investing at full capacity and cease/reduce investments at similar times as in the static scenario. Nevertheless, after this point, the influence of market dynamics becomes apparent. The increasing revenue allows manufacturers to invest for longer horizons into their supplier development programs. In particular, manufacturer two invests longer than manufacturer one. The results show a slight reduction in

investments before each change of generation. At this point, the optimizer already anticipates the spike in revenue and reduces investments to maximize gains. Once the revenue increase stabilizes, the optimizer returns to a regular investment scheme. Moreover, the results show an increase in investments towards the end of the simulation time for all four scenarios. As the supplier's manufacturing costs increase over time, further investments become more beneficial. Finally, the results of market dynamics also show the already known opportunistic behavior for manufacturer two in the simultaneous scenario, resulting in alternating, spiky investments towards the end of the simulation time.

The dynamic mobile phone use case again shows a very different behavior than the previous one. Both manufacturers delay their first investments approximately for the first two years in all collaboration schemes. Therefore, the optimizer determines that the price for investments is too high for the gained benefit of the supplier development program. The comparably low parameter values can explain this behavior for the supplier's manufacturing cost. It is to mention that, for this use case, the relation between the monthly costs for a supplier development project and the willingness-to-pay is approximately half of the automotive use case (factor: automotive 50, mobile phone 26). With this lower relation, we would have assumed to see more substantial investments, as each project only costs approximately half (related to the willingness-to-pay), while the effects remain the same (state increased by one per month with the same learning rate). Thus, the lower number of conducted projects originates from the low value for  $c_{s0}$ , as described above. The observed increase of investments over the simulation time also supports this assumption, as  $c_s(t)$  decreases over the simulation time, first quickly then slowly towards the end of the simulation. While it decreases heavily, manufacturers do not invest or invest only in a few projects. Once the supplier's production cost stabilizes, manufacturers tend to increase their investments to lower these costs further. Moreover, these results follow the same trend as the automotive use case; an increase in revenue generally leads to a nonlinear increase in investments, while decreasing revenue also decreases the manufacturers' willingness to invest. As with the automotive use case, the results show a decrease in investments before or at each model change, resulting from the sudden spike in revenue.

### 5.3. Comparison between Static and Dynamic Assumptions.

Table 2 Depicts the relative differences between the static and dynamics assumptions. As an instance, the mean value for the sum of the revenue of assuming dynamics is 5.2% greater than the equivalent value of static assumption. The values in the table always refer to the sum of revenues for both manufacturers. The results show that an estimation of the system's dynamic behavior achieves the greater sum, i.e., better performance in terms of the overall supply chain revenue.

The results for the automotive use case show an increased profit of approximately 5.0% across all four collaboration schemes, considering the sum of the profits for all

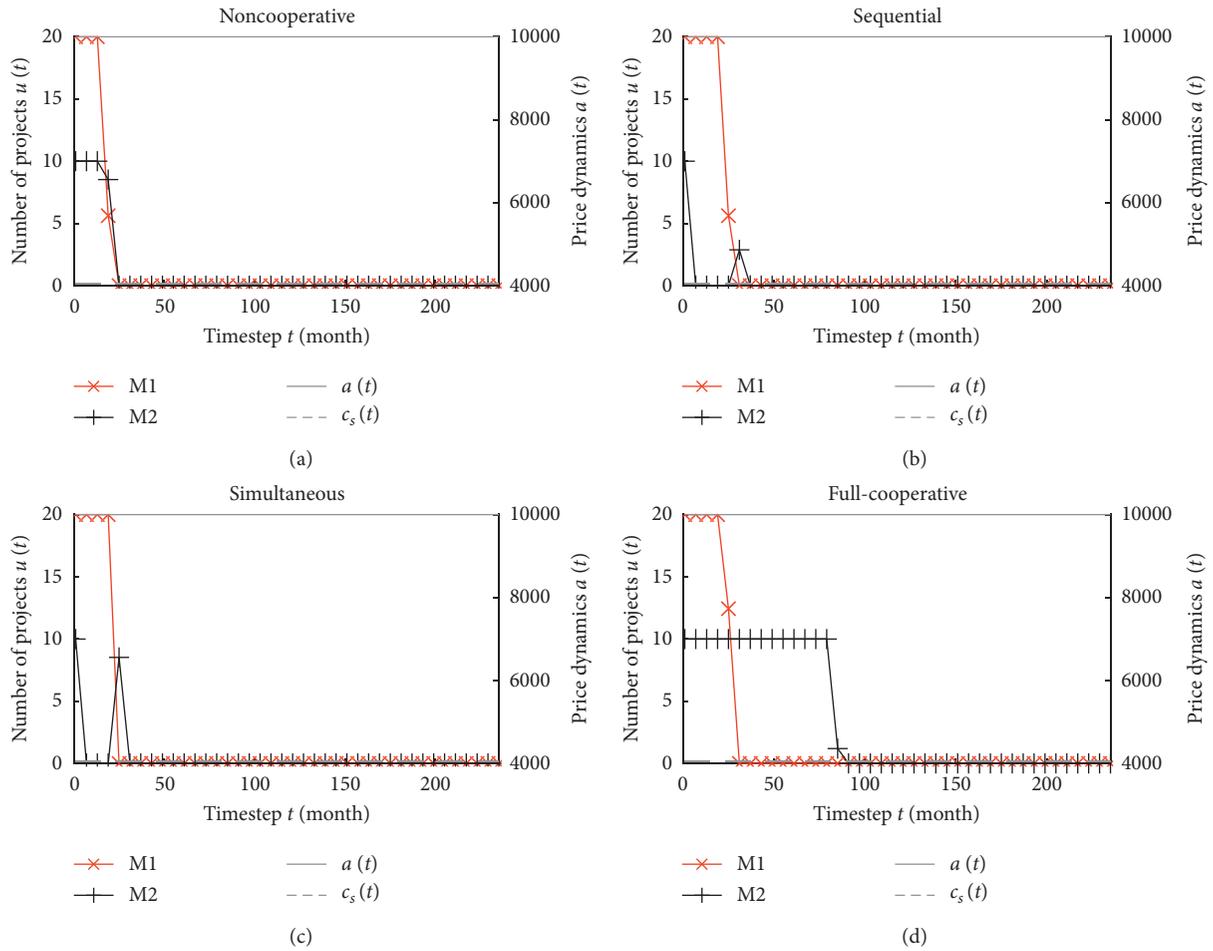


FIGURE 7: Results and for the static automotive use case.

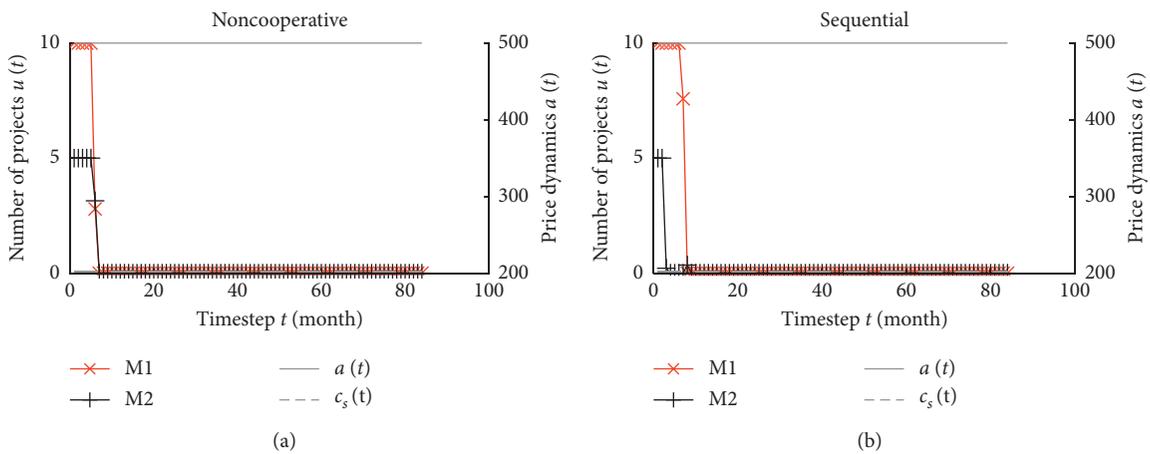


FIGURE 8: Continued.

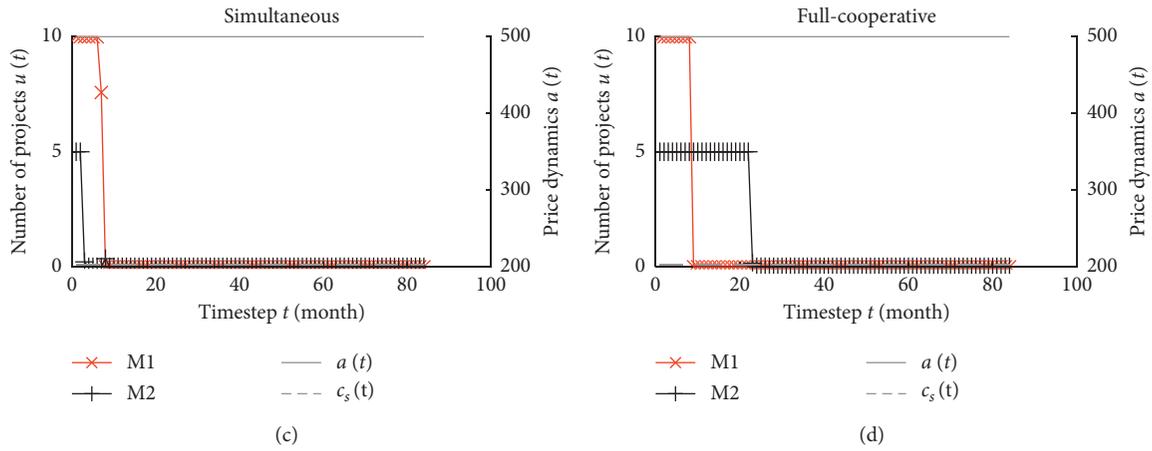


FIGURE 8: Results for the static mobile phone use case.

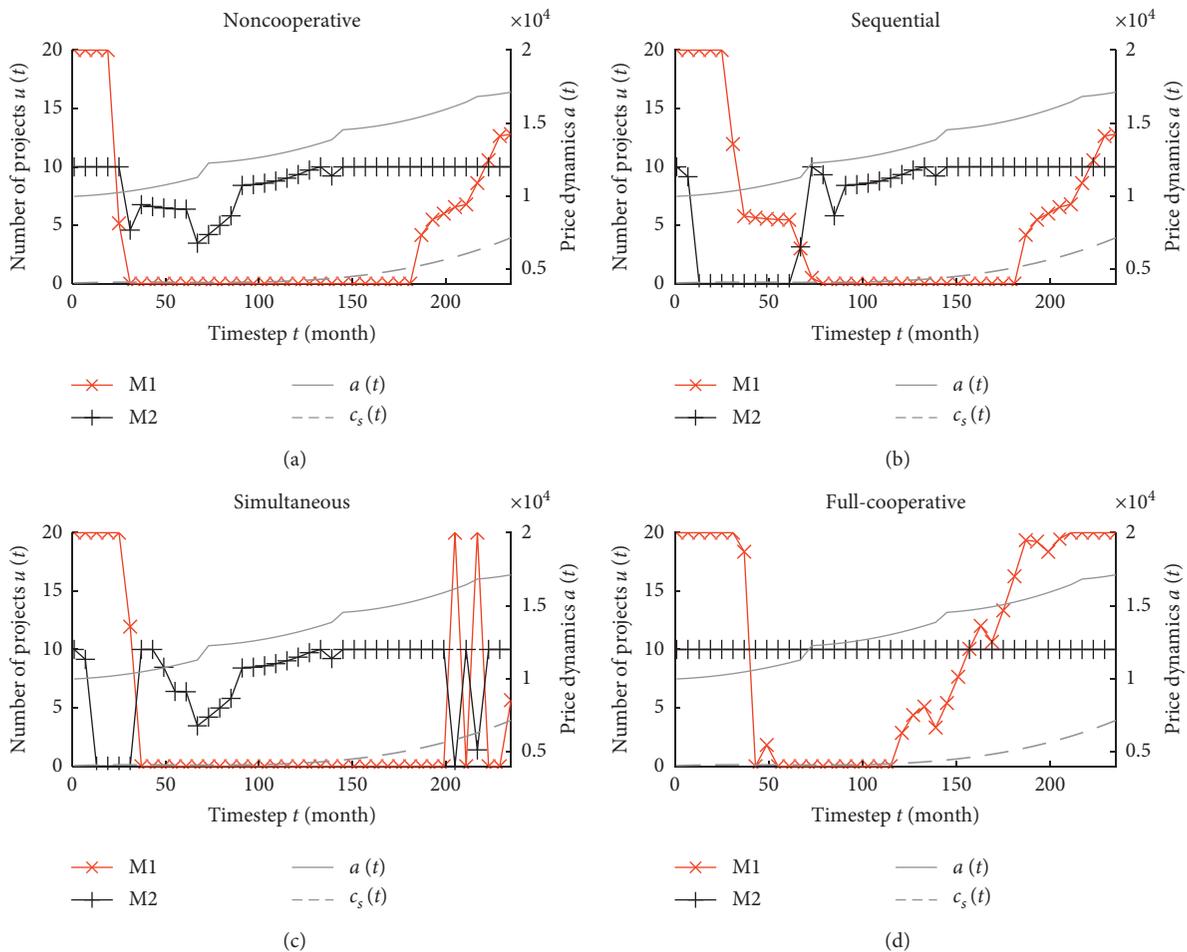


FIGURE 9: Control  $u(t)$  and price dynamics  $a(t)$  for the dynamic automotive use case.

instances. Comparing the global profit for each time instance, the results show that, for early time instances, a static assumption results in higher profit, while an increasing horizon shows an increasing benefit for the dynamic assumption. This is given by the denoted switching point. The

dynamic model assumptions begin to provide a higher global profit starting at 38.5 months into the project on average. When considering the average difference in revenue at the end of the simulation time, the dynamic assumption archives an average of 9.0% more profit compared to the

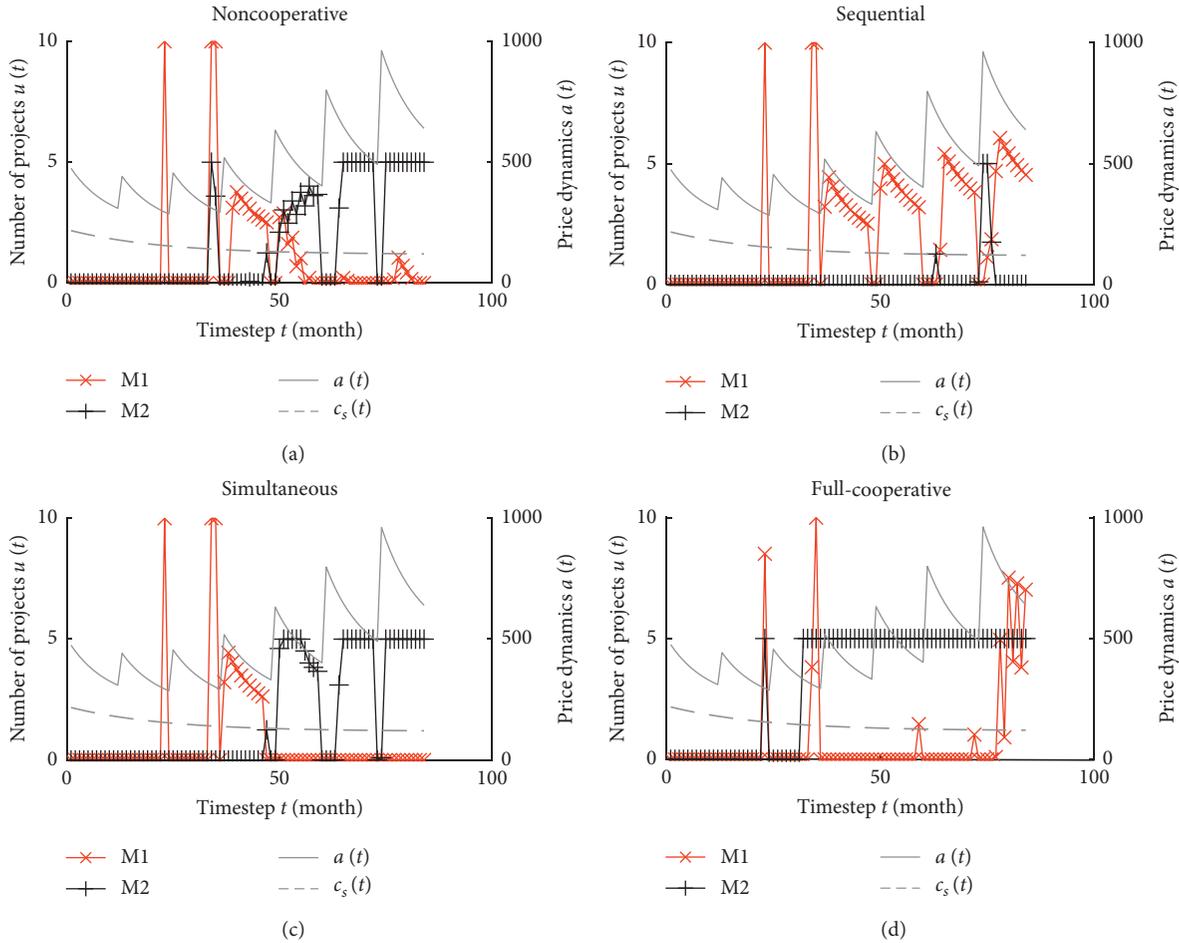


FIGURE 10: Control  $u(t)$  and price dynamics  $a(t)$  for the dynamic mobile phone use case.

TABLE 2: Comparison of static and dynamic model assumptions.

	Noncooperative	Sequential	Simultaneous	Full-cooperative	Mean
Automotive					
Sum of revenue	5.70%	6.00%	6.14%	2.25%	5.02%
Switching point	31 months	37 months	43 months	43 months	38.5 months
Last year (2 instances)	9.59%	10.07%	10.54%	5.70%	8.98%
Last instance	10.42%	10.92%	10.93%	6.33%	9.65%
Mobile phones					
Sum of revenue	1.45%	1.27%	1.59%	-0.24%	1.02%
Switching point	60 months	60 months	60 months	Never	60 months
Last year (12 instances)	2.30%	2.29%	2.31%	2.25%	2.29%
Last instance	1.03%	1.03%	1.03%	0.99%	1.02%

static assumption when considering the last year and even 9.7% when only considering the final instance.

In contrast, the results for the mobile phone use case show no huge difference between the assumptions. The results show a minimal increase of 1.0% in the total profit across all collaboration schemes, again, considering the sum of profits for all instances. Comparing the relative difference in the global profit by time instance, the results show the same behavior as before for the first three collaboration schemes in Table 2. Again, the static assumption shows minor advantages in early instances, whereas the

dynamic assumption tends to increase the overall revenue in later project stages, starting from month 60 (switching point). The full-cooperative scheme shows no switching point, indicating that both assumptions alternate to provide a higher profit when comparing single time instances. Only considering the last year of simulation time, the overall profit differs by 2.3% in favor of the dynamic assumption if averaging all collaboration schemes. This advantage only makes up for approximately 1%, considering the last time instance, indicating a strong variance in the results.

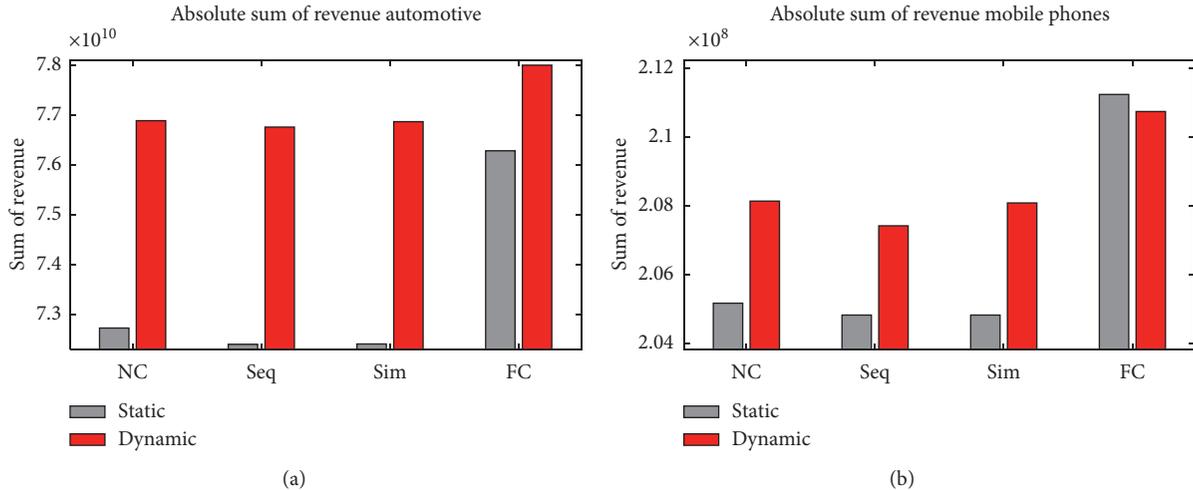


FIGURE 11: Absolute sum of profits for the (a) automotive and (b) mobile phone use cases.

Even though the comparison shows a lower relative increase in revenue for the full-cooperative scheme when the algorithm considers dynamics, the absolute numbers still show that the full-cooperative scheme achieves the highest total revenue in all cases. Figure 11 depicts the absolute value of the sum over revenues across all instances for each collaboration scheme. Even if the dynamic assumption results in slightly less revenue in the full-cooperative mobile phone use case, this figure shows that assuming market dynamics generally results in higher total revenues.

## 6. Discussion

The results show that assuming dynamics during the optimization results in higher or at least close-to-equal revenues for most of the scenarios. Only the full-cooperative mobile phone use case shows a slight decrease in revenue compared to a static assumption. Generally, the results show that the advantage of assuming dynamics depends on the planned runtime of the overall supplier development program. For short programs, a static assumption yields better revenues, as the optimizer issues investments quickly at the beginning of the project. Nevertheless, for more extended programs of more than three years for the automotive use case and more than five years for the mobile phone use case, the integration of dynamics shows higher revenues consistently. Generally, the number of projects funded ties to the supplier's production costs and the current market price (willingness-to-pay  $a$ ) of the product. The optimizer tends to issue more projects, the higher either value grows.

The fact that the full-cooperative schemes benefited the least from assuming dynamics while simultaneous schemes benefitted the most shows an interesting result. This fact, combined with the overall higher revenue of full-cooperative schemes, shows that the combination of cost functions generally provides higher potential to increase revenue in such multimanufacturer scenarios. The sequential scenarios benefit highly from dynamic assumptions but still fall short in the comparison of the overall revenue. As described

above, this setting tends to support opportunistic behavior by the second manufacturer. This manufacturer is not as dependent on the supplier as the first one and often tends not to invest and rely on the first manufacturer's investments. While this optimizes its profit locally, both manufacturers generate less revenue globally. The same holds for the sequential collaboration scheme, which also falls short on total revenue even behind the noncooperative scheme.

The results further show a drastic difference between the two selected use cases. These use cases show very distinct characteristics: a monotone increase in the willingness-to-pay and a decrease in the supplier's production costs for the automotive scenario, compared to a highly volatile willingness-to-pay and an increased production cost for the mobile phone use case. While the automotive use case benefits strongly from the inclusion of dynamics, the mobile phone use case only benefits slightly. The general magnitude of the dynamics can explain this difference. Even though the mobile phone use case shows high fluctuations in the willingness-to-pay, the general magnitude of the changes only amounts to a fraction of the magnitude for the automotive case ( $\sim 2\%$  of the corresponding increase of the willingness-to-pay over the simulation time). To evaluate this theory, we conducted several additional optimizations with uniformly scaled values for the willingness-to-pay and different prediction and sampling horizons. All of these optimizations showed very similar results (approximately  $\pm 2\%$ ) when comparing the sum of the total revenue. While this in itself is no proof for this assumption, it indicates only a minor dependence on the actual parameters used in the experiments but a vital influence of the underlying market dynamics.

## 7. Summary, Conclusion, and Future Work

This article aims to evaluate, if assuming market dynamics within supplier development programs proves advantageous for the application of a dynamic contract extension. Therefore, the article first presented the used optimization

approach, applying Model Predictive Control to optimize supplier development programs for different collaboration schemes in a multimanufacturer setting. The article then presents an extended version of the used cost function, which allows the integration of market dynamics for the parameters  $a$  (willingness-to-pay),  $c_m$  (manufacturer's production costs), and  $c_s$  (supplier's production costs). For the evaluation, the article uses real-world data from Germany's Federal Office for Statistics to establish models for the market dynamics in two use cases: an automotive use case considering the Mercedes A-Class as an example and a mobile phone use case, focusing on the Samsung S-Series. The article presents the results of 16 different scenarios to compare the effects of assuming dynamics (automotive/mobile phone, static/dynamic, and four collaboration schemes).

In general, these results show increased efficiency of the supplier development program if considering current market dynamics. Thereby, the extensions to the approach for optimizing investments in supplier development proposed in this article allow practitioners to render decisions using comparably simple models of the assumed market dynamics. As described in Section 3, this article proposes to modify the actual optimization to use distinct models, in this case, regression models, for the dynamics. While this article uses commonly available data from the Internet, i.e., listing prices for the willingness-to-pay and statistical data from Germany's Federal Office for Statistics for the production costs, companies can also rely on their data and predictions to derive these models. Consequently, they can adapt the underlying market dynamics to their concurrent use case without the need to alter the overall optimization or the mathematical formulation.

Future work will focus on the evaluation of different types and magnitudes of dynamics. The current results show an advantage of including dynamics, but this article also shows that obtaining suitable models for market dynamics is not an easy task. A more detailed analysis of different types of dynamics will support companies in deciding if it is worthwhile to establish such models. Moreover, future work will focus on extending the current formulation of the optimization problem. For example, the current results show a decrease in investments before a new product generation emerges. While this behavior is currently unintended, it is sensible from an economic point of view to cease investments in "old products." We can facilitate such behavior by including different types of supplier development projects. As stated in the state of the art, projects can have different aims, e.g., to provide additional training or resources of general nature, or they can support specific products or components. By implementing this difference, we can apply advanced mechanics to estimate the effect of such projects. On the one hand, it is possible to weigh their effects differently; on the other hand, we could reset product-specific investments on generation changes. Moreover, such differentiation could also help to gain further insights into the interaction of manufacturers. Therefore, we can assume that product-specific investments do not, or only marginally, benefit the other partners, while general projects will benefit both partners to a certain degree.

## Data Availability

The data used to support the findings of this study can be obtained from the website of Germany's Federal Office of Statistics or the provided references.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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