NUMERICAL STUDY ON EVALUATION OF MARKET DYNAMICS IN SUPPLIER DEVELOPMENT

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ABSTRACT

Supplier development describes the attempts of an original equipment manufacturer's to enhance the capabilities and performance of its supplier. These improvement attempts aim at a variety of aspects like quality management, product development, delivery time, and cost reduction. Since supplier development requires the investments of manufactures, it is essential to allocate these investments optimally to minimize risk while maintaining an acceptable level of return. One approach for minimizing the risk of supplier development is to find the optimal length of such an investment. In this research, we aim to evaluate the optimal length of supplier development programs by considering markets dynamics. Since today's markets are highly volatile and dynamic, manufacturers have to take these rapid changes into account to remain competitive. The results of this study show that long-term market dynamic prediction works appropriately in volatile markets; however, it fails in the stable markets, as the optimizer disregards smooth changes in stable markets.

Keywords: supplier development, market dynamics, Model Predictive Control, prediction, estimation.

1 INTRODUCTION

One of the most significant paradigm changes in modern companies' management is that businesses no longer compete independently, but preferably within supply chains (Lambert 2008). In other words, to compete effectively in today's world market, an enterprise must have a network of efficient suppliers. Supplier development provides an opportunity to shape and maintain such a network and create different potentials of their suppliers to face the increasing competitive challenges (Hahn et al. 1990). As an instance, Jin et al. (Jin et al. 2019) noted that automotive manufacturers' competitiveness highly depends on the relationship with their suppliers, and higher investment in supplier relationships is specifically recommended as the market competition increases.

Supplier development generally refers to any contribution by a buying company to improve a the performance and capabilities of a supplier to meet the OEM's short-term and/or long-term supply needs (Krause 1999). These needs are in terms of responsiveness, product or service quality, reliability, delivery time, new technology adoption, or generally in terms of cost (Humphreys et al. 2011, Govindan et al. 2010). Since supplier development provides an effective tool to initiate strategic and competitive advantages for the entire supply chain, OEMs try to originate, design, and carry out supplier development activities (Krause and Ellram 2014). Noshad and Awasthi conducted a literature and practice review of the supplier development context. They pointed out that in 2013 almost 70% of OEMs across the automotive, aerospace, and electronics industry were engaged in supplier development investments (Noshad and Awasthi 2015).

Over the past decades, supplier development absorbed increasing attention in research and practice as a new concept. As an instance, several studies focused on the investigation of the implementation of supplier development in various industries, e.g., (Talluri et al. 2010, Dastyar and Pannek 2019, Bai and Sarkis 2016, Sako 1992, Routroy and Pradhan 2013). According to these studies, Toyota started preparing on-site support to engage suppliers in the Toyota Production System (Sako 1992). Boeing, Chrysler, Daimler, Dell, Ford, General Motors, Honda, Nissan, Siemens, and Volkswagen have taken this collaborative procedure to develop suppliers' performance or capabilities in order to tackle the increasing competitive challenges (Routroy and Pradhan 2013).

2 STATE OF THE ART

Many researchers tried to evaluate the efficiency of supplier development investment since this investment, like any other type of fundings, contains risk. In terms of quantitative evaluations of supplier development, some authors proposed models to evaluate the efficiency of supplier development programs. Bai and Sarkis implemented different game-theoretic models, to show how profits of supplier development investments are influenced by multiple relationships among OEMs and suppliers. The results revealed that the cooperative relationship is economically beneficial to the supply chain. However, it requires more investments and knowledge capital than a non-cooperative relationship (Bai and Sarkis 2016). Talluri et al. proposed two scenarios: one consisting of a single manufacturer and multiple suppliers, and the other one consisting of two manufacturers and multiple suppliers. They studied the supplier development problem from a long-term investment perspective. In the two-manufacturer scenario, they assume that through cooperation, an OEM can gain benefit from the other OEM's investment, whereas, in a non-cooperative situation, an OEM benefits only from its own investment. Similarly, the two cooperative manufacturers will face an equal level of shared risk (Talluri et al. 2010).

Many researchers proposed models of supplier development based on long-term investments. However, current turbulent market conditions like shorter product life-cycles and volatile markets require flexibility in such supplier development programs. To deal with the dynamics of the markets and to find a trade-off between the interests of short-term and long-term supplier development contracting Worthmann et al. (2016) and Proch et al. (2017) established the application of a receding horizon technique. This method proposes a long-term plan for supplier development activities, but only implements a part of it in each time step. Their proposed 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 concentrated on a monopolistic constellation of a single manufacturer and a single supplier. Moreover, the proposed models assume stable and unchanging markets where no external changes occur.

In reality, such changes can have several reasons—for example, the involvement of a supplier with additional competitors or the general market dynamics mentioned above. Consequently, Dastyar and Pannek expanded the described method to a multi-manufacturer scenario, implementing different game-theoretic collaboration schemes to assume the dynamics introduced by additional OEMs (Dastyar and Pannek 2019). They considered a centralized and a distributed setting with two OEMs and one supplier. By applying Model Predictive Control, they simulate and minimize the risk of future investments. MPC provides the opportunity to recurrently decide on the current period based on the current state of the program but also uses predictive models to estimate future development (Dastyar and Pannek 2019).

Additionally, Dastyar, Ripple, and Freitag (2020) presented an evaluation of possible revenue gains in these different collaboration schemes under the assumption of market dynamics. Therefore, the authors modified the modeled cost function to obtain time-dependent values for the product's market price. In an extension of this work, this article proposes a reformulation of the MPC's underlying system models and the accompanying simulation of the "real-world market," to allow a separation of the market simulation and the optimizer's predictions. Hence, it is possible to distinguish the differences between predicting dynamics during the optimization and simulation of the market dynamics. As mentioned above, receding horizon techniques allow estimating a long-term plan for the supplier development program, while facilitating a frequent reevaluation. This article aims to investigate the prediction quality of the proposed model under market dynamics. Furthermore, this article provides an evaluation of the effects of different prediction horizons in the context of extending the overall supplier development investment. The following section briefly depicts a model for the dynamic extension of supplier development program.

3 MODEL AND SOLUTION ALGORITHM

This article builds upon the model presented in (Worthmann et al. 2016, Grüne and Pannek 2017) and its extensions presented in (Dastyar, Ripple, and Freitag 2020). The latter includes market dynamics by assuming that some of the described parameters can change over the time (Dastyar, Ripple, and Freitag 2020). Variable manufacturing costs divide into three broad categories: direct materials costs, direct labor costs, and manufacturing overhead (Ostwald and McLaren 2004). According to the descriptions provided above, the cost function contains three terms, which should be adapted to include market dynamics: the customers' willingness-to-pay (a) and the production costs of the manufacturer (c_m), and of the supplier (c_s). We consider these parameters as time-dependent, to represent gradual changes in these values over time. Afterward, it describes the modifications required to include market dynamics into the proposed approach, resulting in an adapted cost function J as given in Equation (1).

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

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.

Please refer to (Worthmann et al. 2016, Dastyar and Pannek 2019, Dastyar et al. 2020, Dastyar et al. 2020, Dastyar and Pannek 2020) for a more detailed description of the cost function and its origins. To find the optimal supplier development investment horizon, we apply Model Predictive Control (MPC), which allows us to establish optimal control under high dynamics (Pannek and Worthmann 2014). See, for example, Grüne and Pannek for details about this control scheme as well, as for, applications (Grüne and Pannek 2017).

In contrast to the original formulation, which reevaluated the time-dependent parameters during each time step of the optimization, we propose to store these values as part of the optimizers state vector. This way, we can freely decide to update these values in every step (predict dynamics) or just update them every time the program gets reevaluated. The latter case represents the fact that the company participates in a dynamic market, but only measures the current each time they update their supplier development program. The remainder of this article denotes this case as "simulate dynamics" as it simulates dynamics as part of the market simulation but does not predict them as part of the optimization.

3.1 Applied Cases

Following Dastyar, Ripple, and Freitag (2020), we consider two types of highly demanded products with different market conditions to investigate the effect of market dynamics on the optimal lengths of supplier development investments. We study Samsung smartphones' market as highly dynamic and short life-cycle products and Mercedes Benz A-class automobiles as a middle life-cycle product with relatively low-speed market changes, as these markets show very distinct features (Figure 1).

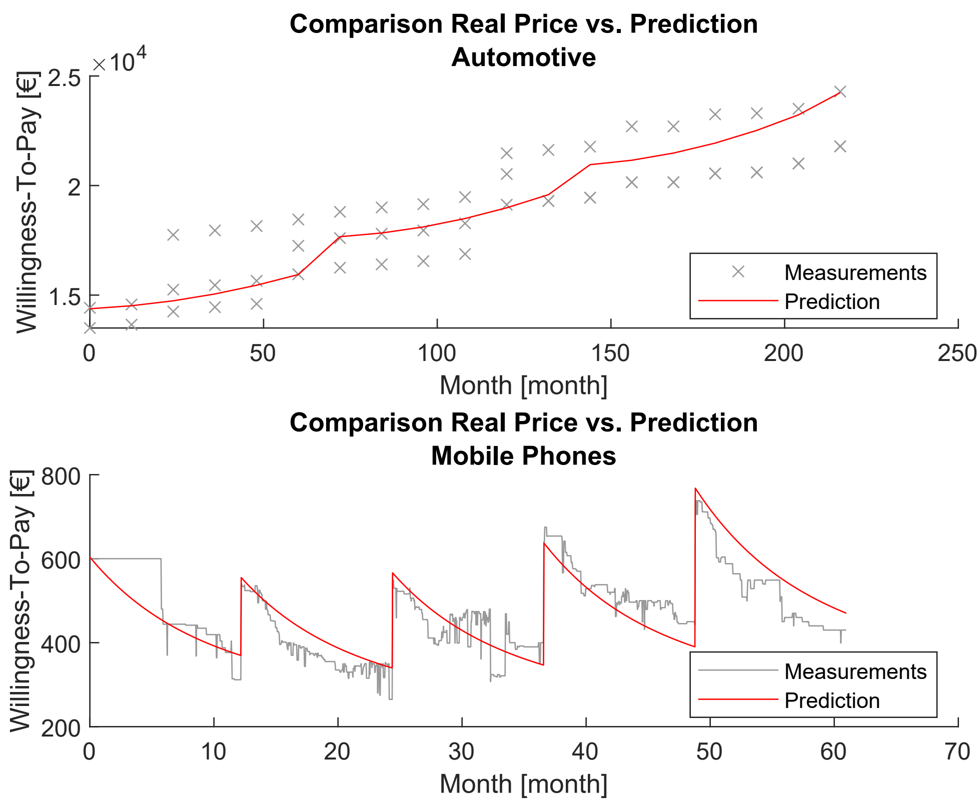

Figure 1: Price development for products in the automotive and mobile phone use-case (Dastyar, Rippel, and Freitag 2020)

The data sets for the production costs come from the database of Germany's Federal Office for Statistics (Statistisches Bundesamt) for both use-cases. To do the numerical experiment, we gained the regression function-driven from product cost (willingness to pay) of both use-cases data, which is shown in red color in Figure 1. In this study the proposed regression model is used as the prediction of products' costs over time.

3.1.1 Mobile Phone Use-case

The considerable number of manufacturing, specifically high technology industries, are active at high speed with rapid transitions markets. The mobile phone industry is one of the most obvious examples. The global mobile phone industry is dealing with structural and progressive changes from its inception at the beginning of 1980 (Giachetti 2013). Quickly changing market dynamics, such as increasing market penetration, intense global competition, and the request of responding swiftly to technological changes, decreasing product life cycles, and huge consumer preferences have continuously structured this industry over time (Rice and Galvin 2006). In the last two decades, the fast introduction of new product technologies and the high demand for products with unrelated capabilities have transformed the mobile phone market into a turbulent market (Giachetti and Gianluca 2010). Mobile phones, as many high-technology products, subject to short product life-cycles, short life on the market, a high steep decline stage, and the lack of a maturity stage (Popper and Buskirk 1992).

3.1.2 Automotive Use-case

Automotive companies face changes caused by globalization, environmental concerns, new governmental regulations, and advances in drive technologies and electronic motors (Cao et al. 2009). Many studied have been conducted about the automotive industry. As an instance, Cao et al. investigated the automotive life-cycle management using RFID. They proposed a three-stage life cycle for automobiles: beginning-of-life (BOL), middle-of-life (MOL), and end-of-life (EOL). Beginning-of-life is the stage of the automobile's design and manufacturing. The middle-of-life refers to the phase of emerging, selling using, and repairing of the automobile when it is necessary. The final phase, end-of-life, refers to the stage when automobile releases for decommissioning after being used by costumer (Cao et al. 2009). In the current study, we only consider the MOL stage of the cars' and mobile phones' life-cycles (emerging the product to the market). Based on the MOL stage, cars represent a middle life-cycle product, while mobile phones represent a short life-cycle product.

The market situation of mobile phones and automobiles are different based on product life-cycles and market dynamics. The market price of mobile phones generally decreases considerably when the new model releases to the market. However, automobile prices change in the market slowly when a new model presents to the market. Furthermore, automobiles prices remain comparably stationary when compared to the high dynamics of mobile phone prices.

The following subsection presents the differences among proposed experimental scenarios with considering and without considering market dynamics during the optimization.

3.2 Experimental Design

For the evaluation of market changes, this article employs the same market dynamics and scenarios as defined in (Dastyar, Ripple, and Freitag 2020). Table 1 shows the parameters applied in the optimization.

We compare the result of different lengths of supplier development investments based on three scenarios. These scenarios are defined as follows:

- **Without Dynamics:** optimizing the length of supplier development programs without considering markets' dynamics. However, the non-dynamic scenario is not realistic, but it plays the rule of baseline for the results of the optimizer.

Table 1: Experimental setup

Parameter	**Description**	**Automotive**	**Mobile Phones**
a_0	Initial willingness-to-pay	10,000	500
c_{sd}	Cost for SD projects	3,000,000	13,000
c_{m0}	Initial prod. cost for manuf.	4,500	225
c_{s0}	Initial prod. cost for supplier	4,050	202.5
b	Price elasticity	0.01	0.01
r	Revenue of supplier	450	22.5
m	Learning rate	-0.1	-0.1
p	Maximum number of SD	20	10
–	Sampling step width	6	2
–	Planning periods	3 ,6 ,12	3 ,6 ,12
–	Simulation horizon	25*6	25*2

- **Simulated Dynamics:** optimizing the length of supplier development investment based on the simulated market's dynamics. It means applying fixed parameters' value per time steps for the optimizer and updating the parameters' value based on the measured market dynamics for the next step of the optimizer. In this scenario, the optimizer does not anticipate dynamics. Consequently, only the first time step of the optimization adapts to the current (simulated) market situation.
- **Predicted Dynamics:** optimizing the length of supplier development investment based on the predicted market's dynamic. The prediction of the market dynamics for both use-cases assumed as the regression function-driven from the market dynamics shown as red lines in Figure 1. In this scenario, the optimizer predicts price and cost changes for each time step of its optimization.

4 NUMERICAL RESULTS

This experiment evaluates the influence of the selected prediction horizon N on the behavior of the optimizer. We assumed a different prediction horizon as 3, 6, and 12-time steps to experiment. The prediction horizon equal to three acts as a minimum, which determines the current control value (1) and two prediction steps. Figures 2 - 4 and 5 - 7 depict the results for both use-cases and different prediction horizons. Each figure shows the control value, which in this study refers to the number of supplier development projects (black, solid line) and the predicted length of the supplier development program (red, dashed line). This article considers the predicted length as the index of the last time step within the open loop's optimal control sequence, which is larger than zero.

4.1 Results of Mobile Phone Use-case

The mobile phone use-case comprises a highly volatile dynamic. According to the gathered data in every year, a new product is introduced and released to the market. These quick periodic changes result in choosing a small time step width of two months.

Figure 2 shows the results for a very small prediction horizon of three periods (6 months). In this Figure compared the result of without dynamics, simulated dynamics, and predicted dynamics with the others. As it was shown in this figure, with considering the fixed products' market conditions, investment in supplier development is not profitable. Regarding simulated dynamics, the optimizer reacts a bit late to the changes in the market. As an example, the new model of mobile phone (Figure 1) has released to the market at the time 10th month. The simulated dynamics reacted to this change 2-4 months later. However, considering the predicted dynamics (regression model) in the optimizer open-loop causes the exact time reaction of

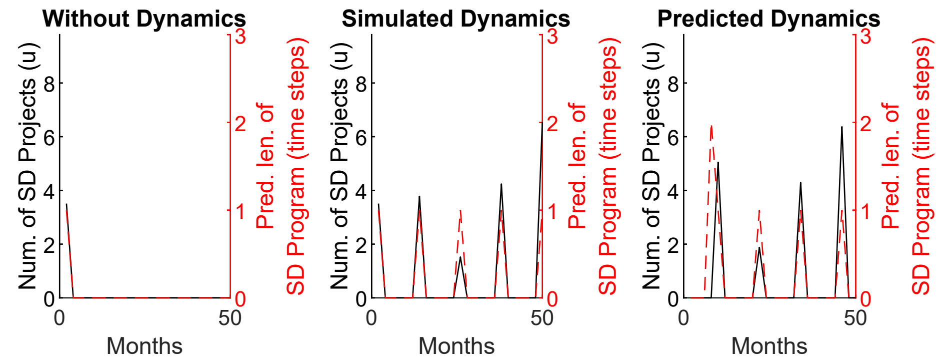

Figure 2: Control and prediction for the mobile phone use-case with $N = 3$

the optimizer to supplier development, in this case, the optimal number of supplier development projects increases before a new model is released to the market, when the current model has the lowest price in its period.

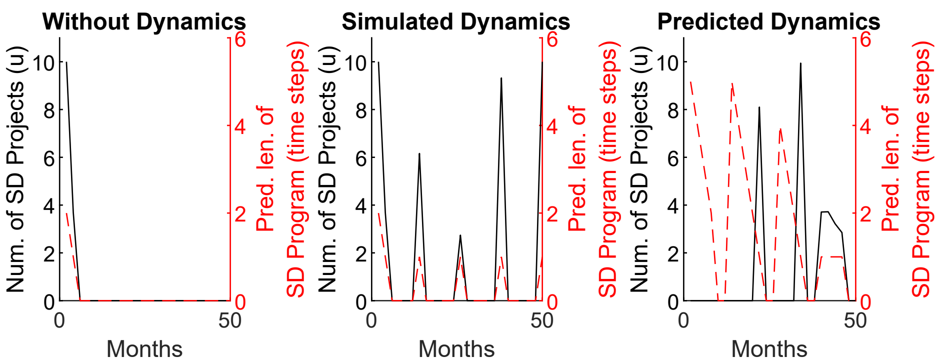

Figure 3: Control and prediction for the mobile phone use-case with $N = 6$

Figure 3 shows the results for the mobile phone use-case with a prediction horizon of $N = 6$ (12 months). It compares the number of investments (number of projects), higher prediction horizon results in more investments per period in all three scenarios. Apart from this, the scenarios without dynamics and simulated dynamics behave similarly as the predicted dynamics for a shorter horizon. In this case, predicted dynamics show different investment behavior. The optimizer delays the first investment, even though it predicts investments during the start of the program. Afterward, it issues larger amounts of investments a little later than the simulated dynamics scenario. In terms of the predictions, the optimizer predicts future investments with a notable pre-warning time. For example, it predicts the investment period between time steps 10 and 12 at time step 7, which is half a prediction horizon earlier—the same accounts for the second investment period. In contrast, the optimizer does not predict the third period, which only comprises low amounts of investments, but only tracks its duration as observed in the case of the simulated dynamics. In between these pre-warnings, the optimizer suggests that the program should not be continued within its prediction horizon for single time steps.

Accordingly, Figure 4 shows the results for the mobile phone use-case with a prediction horizon of $N = 12$ (24 months). As before, the amount of investments increases throughout all scenarios. Apart from this, the behaviors in the scenarios without dynamics and simulated dynamics remain the same as for smaller prediction horizons. The predicted dynamics scenario shows a more defined shape of investments, which more closely follows the product's price development. In terms of the pre-warning time, the optimizer shows the same behavior as before. Even though the optimizer delays the first investment period, the optimizer

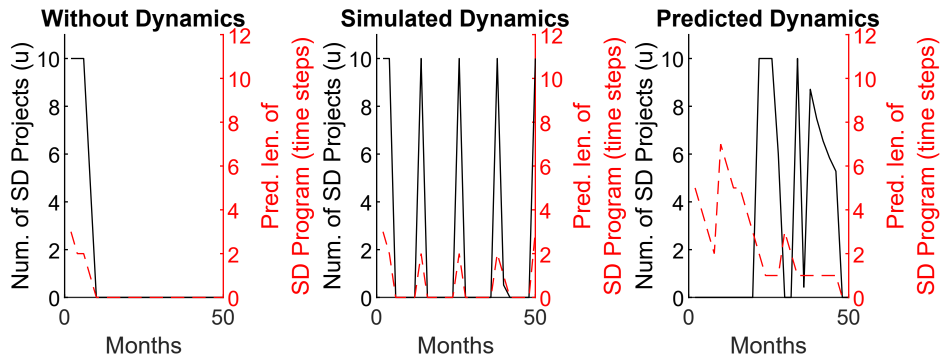

Figure 4: Control and prediction for the mobile phone use-case with $N = 12$

predicts the need to invest. It predicts the first investment period, which takes place between the time steps 10 and 15 at time step 5, a bit earlier than before. The second period is only predicted right before it happens. As a difference to the smaller prediction horizon, the optimizer does not suggest to stop the program in between investment periods but suggests to reevaluate monthly.

4.2 Results of Automotive Use-case

The automotive use-case features slowly but steadily changing market dynamics. In contrast to the mobile phone use-case, the dynamics change by larger amounts and over longer periods. Thus, the automotive use-case uses a larger time step width of six months while autos have a relatively longer life-cycle.

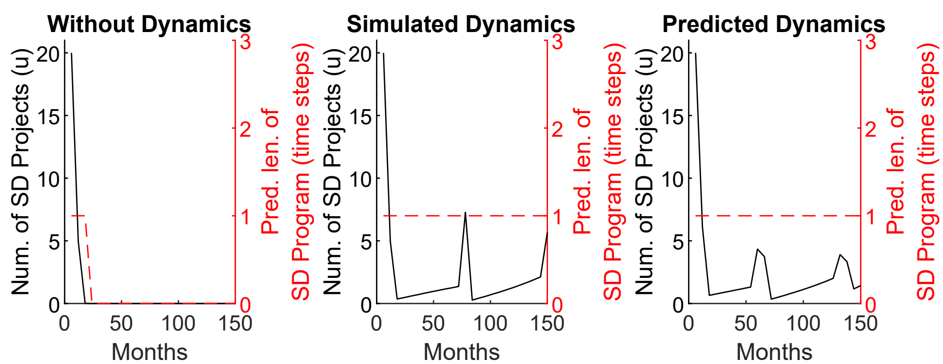

Figure 5: Control and prediction for the automotive use-case with $N = 3$

As with the previous use-case, Figure 5 depicts the results for $N = 3$ (1.5 years). In terms of the investment strategy, the results comply with the results observed in the mobile phone use-case: predicted dynamics scenario results in smoother and earlier investments. Considering the forecasts, both scenarios involving dynamics do not anticipate further investments and show an inability to forecast periods of higher investments. Nevertheless, already with this short prediction horizon, the optimizer suggests future investments in the next time step.

Figure 6 depicts the results for $N = 6$ (3 years). These results mainly differ from the smaller prediction horizon in larger investments and, in case of predicted dynamics, in slightly extended investment periods. As in these scenarios, investments never drop to zero; the segments in between two local minima are considered as investment periods. Noticeably, as the initial investment period extends, the optimizer predicts its duration from the beginning on but does not predict future periods.

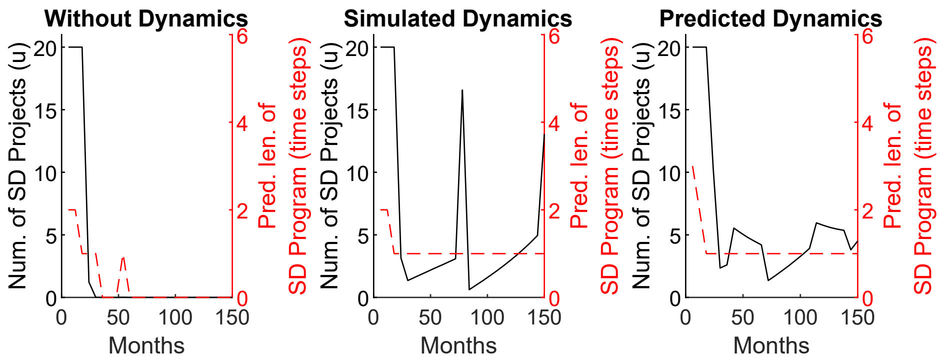

Figure 6: Control and prediction for the automotive use-case with $N = 6$

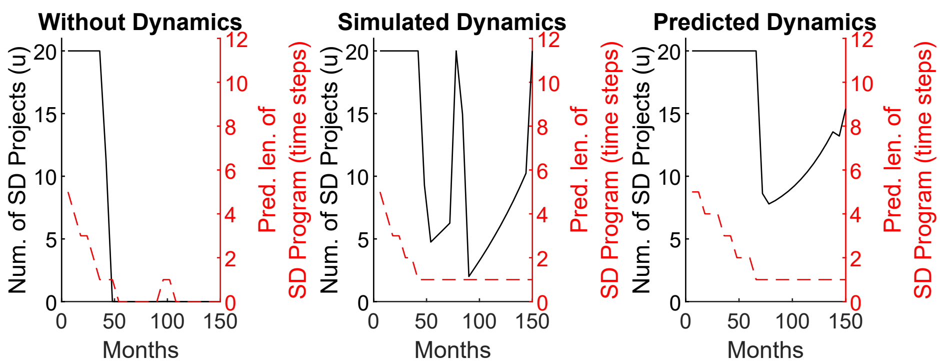

Figure 7: Control and prediction for the automotive use-case with $N = 12$

Finally, Figure 7 depicts the results for $N = 12$ (6 years). These results show the same trends to extended investments and a closer approximation of the product's price development. As in the previous scenario, the optimizer never suggests to cease the program but does not predict future investment periods appropriately.

4.3 Discussion: Effect of the Prediction Horizon

The simulation results revealed that longer horizons provide a better representation of the price development in the dynamic market. At the same time, the optimizer works better in longer horizon experiments since predictions need a minimum horizon to work properly and do not offer a good solution for short horizons. However, a longer horizon of prediction is not as sensitive to changes in the market. It does not suggest to stop investment even if some changes in the market are coming up. The result of the prediction investment of supplier development (dashed-red line) did not react to the optimizer and the market dynamic. It is just extending by 1 in all cases (apart for the beginning in the $N = 12$ setting). The "missing" predictions imply that the optimizer realizes very high investment amounts (basically just the maximum) for future investments. This can be explained by the slow dynamics in the automotive scenario vs. the fast changes in the mobile phone use-case. The changes in market dynamics in the auto are just not high enough (value-wise) to be noted by the optimizer.

4.4 Discussion: Effect of Predicting Market Dynamics

The results show that not predicting dynamics during the optimization results incorrectly predicting current investment periods, at least in the mobile phone use-case. In all cases, the optimizer tracks these periods correctly, but, for small prediction horizons, suggests stopping the overall program as soon as the current investment period ends. In the automotive use-case, the optimizer tracks very high and long investment periods like the one in the beginning. In this use-case, the prediction of market dynamics does not lead to a better forecast. Nevertheless, the same trends towards smoother and earlier investments can be observed with increasing prediction horizons when anticipating market dynamics.

5 CONCLUSIONS AND FUTURE WORK

In conclusion, in the short horizon of prediction in both use-cases, the optimizer reacted to the market dynamics appropriately. In the automotive use-case in the short term evaluation, the optimizer suggests not do start the supplier development up to a certain point. From that point, it offers more investments over more extended periods. In other words, for middle life-cycle products in stable markets, short time supplier development investment is not profitable as in these markets, supplier development investments do not pay off immediately. Therefore OEMs should invest in supplier development for longer horizons to reach the profitable point. However, in the mobile phone market, short-term supplier development investment pays off immediately. Additionally, the results show that long-term prediction works quite well in volatile markets but fails in stable markets. While in the more stable market, optimizer disregard the smooth market changes. Therefore, stable markets do not need predictive control strategies to deal with their market dynamics. Here other dynamics, such as in multi-manufacturer situations out-weight the market dynamics. In contrast, volatile markets can benefit from such an approach to stabilize OEM-Supplier relationships since it enables the model to get market dynamics into optimizer and measure the optimal investment horizon accordingly.

Future work will concentrate on extending the proposed optimization model by considering the dynamics of the market in the case of multi-manufacturer settings. This extension also allows considering the relationship among manufacturers when they would like to invest in supplier development projects in the same supplier, which can provide the base for studying the case when a manufacturer without cooperating with each other or being involved in partial cooperation or full cooperation in developing a common set of suppliers.

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