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A decision aid for Aggregate Production Planning (APP) strategies

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Abstract

Soaring complexity in markets and fast changes of products, technologies and supply chains as well as increasing uncertainty make it nearly impossible to fully integrate all relevant factors and information into decision-making processes in manufacturing. As a result, selection of decision making strategies and their complexity is a pressing issue in production. Aggregate Production Planning attempts to reconcile expected mid-term and short-term demand with equipment, workforce and orders and presents such a key problem. Basic, heuristic solution strategies often reach a very good performance and stand out for their ease of adaptability and integration, rapid response times, computational efficiency, and broad applicability. However, strategy selection is challenging because a comprehensive overview of their efficiency across varying demand and cost scenarios is still lacking. Various demand scenarios are considered in this paper, and the performance of Aggregate Production Planning strategies is evaluated considering factors such as employees, subcontractors, overtime, inventory, and backlog. A decision aid for Aggregate Production Planning (APP) problems is proposed.

Keywords: Aggregate Production Planning; Production Planning and Control; Scenario Analysis; Model Predictive Control

1. Introduction

Shortened product life-cycles and technically more complex products, as well as turbulent and volatile markets and a rise of the frequency in crises, are making production planning increasingly complex and lead to an increased need for fast reactions [1]. Aggregated Production Planning (APP) as one of the fundamental components of production planning represents a key process in the operations of an industrial company [2] reconciling expected short- to medium-term demand with equipment, workforce and supplier usage [3]. It explicitly does not include an adaption of the produced product portfolio but can make use of the flexibility and changeability of manufacturing systems [4]. APP's timescale typically is quarters or months [2] but can extend to weeks or days [3]. It can clearly be differentiated from task assignment on the mechanical level [5] or the planning, layout and design of manufacturing systems [6]. The main driver of uncertainty is the demand, with rising complexity of the environment in which the APP has to be solved leading to the situation that APP either is not solvable by today's optimal solvers [7] or needs great simplifications to become solvable, which in turn does not consider the full complexity of APP [8]. In consequence, simple APP strategies and heuristics often have competitive or even the best outcomes [2]; thus, industrial practice often still relies on gut feeling, rules of thumb or basic APP strategies [8]. While there are already various publications on the different basic APP strategies, their function and usage, there is still little support determining the optimal APP strategy for different manufacturing and demand scenarios [2]. To overcome this gap, this paper analyses different demand scenarios and the performance of the basic APP strategies in them. This paper is structured as follows: Section 2 summarizes related work, followed by the proposed method introduced in Section 3. The results are reported and analyzed in Section 4 to aid in strategy selection. Section 5 discusses the outcomes and impact on future research and application.

2. Related work

To model the production environment and promote applicability to different manufacturing companies and environments, most APPs share a core of basic elements [9]. The optimum most often is characterized by minimizing or maximizing the total cost or profit [10], respectively. The basic APP elements most often used are the workforce cost consisting of long-term

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employees, short-term subcontractors and overtime cost as well as their corresponding productivity [3]. To adapt the workforce level, change costs consisting of hiring and training cost to add new employees and subcontractors and layoff costs to reduce the numbers of employees and subcontractors are added [7]. To shift product and demand from one period to another, inventory and backlog and their associated costs are included [2]. To represent the demand side, a pre-determined market demand and a forecast are used [3]. Additional model variables and cost factors can be added. To solve the resulting APP problem various heuristics as strategies and simplifications are used to linearize this non-linear optimization problem [7]. These approaches are based on four APP production planning strategies or combinations of them [9, 2]. The chase strategy is based on constantly adjusting the workforce size by frequently hiring and laying off employees to match the demand level [11]. The level strategy uses a stable level of employees and adjusts to variations in the demand using inventory and backlog [11]. The overtime strategy also uses a base level of employees but adjust to variations in the demand using overtime (and undertime) [11]. The fourth basic APP strategy, the subcontracting strategy, uses a low stable workforce level and adapts to variations in demand using subcontracted workers which can be temporarily hired and laid-off [2]. Additionally, the strategies can be mixed and hybrid forms can be used [2]. Along with the overview in Figure 1, the reader is referred to Brandenburg (2014) for a classification of other solution approaches [12]. These solution approaches use similar adaption mechanisms as the basic APP strategies but differ in their determination of which mechanism is to be used to what extent in each time step and demand scenario.

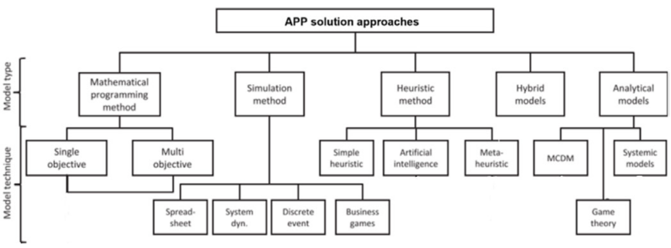

Fig. 1. APP solution approaches, based on Brandenburg (2014) [12]

In Table 1 it can be seen that research today focuses on the mixed chase and level strategy [13]. Buxey (2005) conducted multiple surveys on the usage of APP strategies among operations managers [14] and concluded that most operations manager chose the chase strategy as the preferred strategy. Similarly, Jamalnia and Feili (2013) conclude that the chase strategy is the mainly used APP strategy in industry [14, 8].

The industrial and academic preference is to apply heuristic APP strategies to the APP problem due to their good performance, ease of understanding and robustness [7]. The strong focus on the chase strategy, however, may not be justified. A compelling reason is the lack of support for mapping the right APP strategy to the respective demand and environment. As a result, using a traditional strategy or following the majority is predominant [13]. Therefore, our paper proposes a method for analyzing performance across a wide set of demands and environments, providing a missing decision aid for APP strategy selection.

	Total
Chase strategy	3
Level strategy	3
Mixed chase and level strategy	92
Modified chase strategy	4
Modified level strategy	4
Demand management strategy	1

Table 1. APP strategies reported in the literature, extended from [13]

3. Method for the performance Analysis of the basic APP strategies

To compare the basic APP strategies, demand data for each demand scenario and the APP problem have to be defined first. Additionally, the evaluated APP strategies have to be described as some of them can vary in their concrete application and definition due to possible modifications.

3.1. Demand data sets

To make results as realistic as possible, big data sets with real world demand data are preferred. The largest publicly available datasets are the datasets of the Makridakis-Competitions (M-Competitions). The M-Competitions are a series of empirical studies which compare the performance of forecasting methods [15]. Five M-Competitions, M1 to M5, have been carried out with the M3 Competition being the latest study which included demand data from various real world manufacturing companies [16]. The M3 Competitions 3003 series were selected that are composed of various time series data and different intervals of which 334 are monthly industry data [15]. This dataset is used in the research reported in this paper to obtain typical parameter values for the trend, seasonality and noise for manufacturing companies listed in Table 2

Type	Quantile	Trend	Seasonal	Noise
Low	5%	-0.0046	0.0391	0.0159
Low	10%	-0.0029	0.0508	0.0222
	25%	-0.0005	0.0754	0.0339
Medium	Average	0.0035	0.1912	0.0856
Medium	Median (50%)	0.0029	0.1402	0.0546
	75%	0.0067	0.2376	0.0999
High	90%	0.0135	0.388	0.192
High	95%	0.0187	0.5277	0.253

Table 2. Scenarios derived from the demand data analysis in daily units

Each of the three parameters, i.e. trend, seasonality and noise, is condensed into three categories for possible values: high, consisting of the 95%-quantile to 90% quantile; medium, consisting of the median to average values; and low, consisting of the 5%-quantile to 10%-quantile. The 27 combinations of these categories are used to evaluate the efficacy of the different APP strategies.

3.2. APP problem

The APP problem to be solved is the basic APP scenario of one organization with the goal to maximize its profit, which is the most common industrial model [8]. The variables include the number of employees, the number of subcontractors, the usage of overtime, the number of changes of employees and subcontractors and the inventory and backlog levels and their corresponding cost factors. Additionally, the material cost and miscellaneous cost are added to create a cost scenario close to the real world factors, based on [3, 7]. Due to the short- to medium-term nature of APP the profit maximization over all time periods as an objective is not discounted:

$$\max \sum_{t=N_1}^{N_2} Profit(u_t, x_t) = max \sum_{t=N_1}^{N_2} c_{salesPrice} * Output(u_t) - Cost(u_t, x_t) \quad (1)$$

$$Cost(u_t, x_t) = f_{employee}(u_t) + f_{subcontractor}(u_t) + f_{overtime}(u_t) + f_{change}(u_t) + f_{inventory}(x_t) + f_{backlog}(x_t) + f_{material}(u_t) + f_{miscellaneous}(u_t) \quad (2)$$

$$f_{employee}(u_t) = c_{employee} * u_{employee,t} * h_{employee} * u_{overtime,t} \quad (3)$$

$$f_{subcontractor}(u_t) = c_{subcontractor} * u_{subcontractor,t} * h_{subcontractor} * u_{overtime,t} \quad (4)$$

$$f_{overtime}(u_t) = \frac{\text{sign}(u_{overtime,t} - 1) + 1}{2} * c_{overtime} * (u_{overtime,t} - 1) * (u_{employee,t} * h_{employee} + u_{subcontractor,t} * h_{subcontractor}) \quad (5)$$

$$f_{change}(u_t) = c_{changeEmployee} * |\Delta u_{employee,t}| + c_{changeSubcontractor} * |\Delta u_{subcontractor,t}| \quad (6)$$

$$f_{inventory}(u_t) = \frac{\text{sign}(x_{inventoryBacklog,t}) + 1}{2} * c_{inventory} * x_{inventoryBacklog,t} \quad (7)$$

$$f_{backlog}(u_t) = \frac{\text{sign}(x_{inventoryBacklog,t}) - 1}{2} * c_{backlog} * x_{inventoryBacklog,t} \quad (8)$$

$$f_{material}(u_t) = c_{Material} * Output(u_t) \quad (9)$$

$$f_{miscellaneous}(u_t) = c_{miscellaneousPerProduct} * Output(u_t) \quad (10)$$

The output is calculated as follows:

$$Output(u_t) = u_{employee,t} * h_{employee} * u_{overtime,t} * o_{employee} + u_{subcontractor,t} * h_{subcontractor} * u_{overtime,t} * o_{subcontractor} \quad (11)$$

From this the inventory and backlog level can be calculated:

$$x_{inventoryBacklog,t} = x_{inventoryBacklog,t-1} + Output(u_t) - x_{demand,t} \quad (12)$$

Additionally, the possible overtime has to be restricted to follow work laws [7]:

$$u_{overtime,MIN} \leq u_{overtime,t} \leq u_{overtime,MAX} \quad (13)$$

$$u_{employee,t}, u_{subcontractor,t} \in \mathbb{N}_{\geq 0} \quad (14)$$

$$u_{overtime,t} \in \mathbb{R} \quad (15)$$

3.3. Cost factors

To represent real-world scenarios, the cost and production factors are based on the studies by May et al. (2023) [3, 7]. In the manufacturing sector the overall salary costs including social costs that result from employing people sum up to an average of 18.4% of the gross production value (GPV) [17]. The cost of employees is 20€/hour and the productivity of the employees is 4 products per hour. To simulate a difference in experience and, thus, work efficiency the productivity of subcontractors is set lower than the employees productivity to 3.5 products per hour according to industrial practice. Jacobs and Chase (2018) suggest overtime cost of 50% and in exceptional cases 25% [2], which is confirmed by industrial studies [7]. Therefore, 50% is assumed as the extra cost for overtime while 25% is used to analyze the effect of cost factors as described in Section 4.2. For the change cost of employees and subcontractors the cost per employee is 300€ and the cost to change a subcontractor is 150€ [7]. The average inventory cost in the United States is 30% to 35% of the inventory item per year [2]. Per month, this means costs of 2.5% to 2.9%. As the items are not held for a whole month due to the continuous demand and manufacturing this is adjusted to 1.67% per month. Backlog cost is hard to estimate. Therefore, the backlog cost is set to the same value as the inventory cost [7]. The material cost for manufacturing companies sum up to 58.4% of the total cost [17] which is used to derive per part material costs. Miscellaneous costs include cost for rental and lease contracts, external services, depreciation of machinery and others and sum up to around 18.6% of the total cost [17]. The cost factors used are listed in Table 3.

Cost factors	Average Manufacturer (%)	Used cost (€)
Material and trade goods	0.584	18
Wage (Employee)	0.184	5
Wage (Subcontractor)	0.2453	5.71
Change cost (Employee)		300
Change cost (Subcontractor)		150
Over-Undertime	0.292	2.5
Inventory - Output	0.0167	0.5
Backlog cost	0.0167	0.5
Miscellaneous	0.186	5
Sales price	1	30

Table 3. Cost factors for the standard scenario

To analyze the influences of the cost factors, additional cost scenarios are run in which one cost parameter is set lower or higher than in the standard scenario. These cost scenarios are presented in Table 4.

3.4. APP Strategies

The APP strategies used for performance analysis are based on the basic APP strategies described in Section 2. The periods are set to months in this study. The *chase strategy* adapts the number of employees every month based on the current month's demand. As employees cannot be split and each produces multiple products per month, production cannot exactly match the demand and the small difference is buffered with inventory and backlog. The *level strategy* takes the forecast of the next longer period, here a year, consisting of the 12 next monthly periods, and calculates the average expected demand while taking the current inventory and backlog level in account.

Scenario name	Changed Cost parameters	New values (old)
Low Inventory/Backlog cost	Inventory cost Backlog cost	0.1 (0.5) 0.1 (0.5)
High Inventory/Backlog cost	Inventory cost Backlog cost	1 (0.5) 1 (0.5)
High Change cost Employees	Change cost Employee	600 (300)
High Overtime cost	Overtime cost	10 (5)
Low Output	Output Employee Output Subcontractor	4 (2) 3.5 (1.75)

Table 4. High and low cost scenarios

This is then used to set the number of employees. The difference between that expected average demand level and the actual demand level is then buffered with inventory and backlog. The *overtime strategy* takes the forecast of the next longer period, a year, and calculates the average expected demand while taking the current inventory and backlog level in account. This is then used to set the number of employees. The difference between that expected average demand level and the actual demand level is then buffered with overtime. If the amount of overtime would need to be higher than the maximal overtime level or lower than the minimal overtime level inventory and backlog is used to buffer the rest. The *subcontractor strategy* takes the forecast of the next longer period, a year, and takes the expected minimal value as the number of employees. If the current period's demand exceeds the expected minimal value, subcontractors are used to match the demand as closely as possible. As subcontractors cannot be split and one subcontractor produces multiple products each month, it cannot perfectly match the demand, the small difference is buffered with inventory and backlog and if the demand level is below the expected minimal value the subcontractor level is set to 0 and inventory is used. To investigate the influence of the interpretation and execution of this APP strategy, an additional subcontractor strategy, the *quantile subcontractor strategy*, is implemented which uses the 25%-quantile for the employee level.

4. Results and decision aid

As visualized in Figure 2, the influence of the demand parameters on performance is significant. Areas, highlighted in orange to yellow indicate significant performance loss compared to the best performing strategy. In the standard cost scenario in Table 3, without demand knowledge, the *overtime strategy* performs acceptably.

4.1. Standard-scenario

The *overtime strategy* performs best in the demand scenarios in which the noise and trend are low and medium, while the *chase strategy* performs best in the medium to high noise and medium to high trend scenarios as visible in Table 5 in which first the profit is reported, followed by the relative performance compared to the best strategy in the specific case. The profit is calculated as the cumulative profit during the evaluation period in EUR. Comparing the performance of the different strategies over the different demand scenarios it can be concluded that the *chase strategy* improves with higher trend and slightly improves with higher noise. The *level strategy* improves with a higher trend and worse with higher season levels. If the noise level increases the *level strategy* improves slightly as well. The *overtime strategy* performs well in stable scenarios but performs worse with higher trends and higher noise levels. The *subcontractor strategy* performs better with higher trend.

Overall, if the *subcontractor strategy* is compared to the *subcontractor quantile strategy* it can be seen that the quantile strategy performs better in 21 of the 27 scenarios and mainly performs worse in the low noise and high trend scenarios and in some of the medium noise and medium to high trend scenarios, highlighting the importance of careful fine-tuning.

4.2. Cost factor analysis

In the *low inventory and backlog cost scenario*, the level strategy dominates most of the demand scenarios except for the low trend and low noise scenarios in which the subcontractor strategy dominates, as well as low noise and high trend scenarios in which either the chase or the overtime strategy perform better. This outcome is not surprising as the level strategy uses the inventory and backlog as its key adaption factor. The better performance of the subcontractor strategy in the low trend and low noise scenarios might be explained by the low change in demand in between periods, which delays the usage of inventory and backlog strategy. The better performance of the overtime and chase strategy in low noise and high trend scenarios might be explained similarly as a steady trend leads to the level strategy building up inventory during the first half of its employee level adaption period while it only uses it up during the second half of the adaption period.

The outcome of the *high inventory and backlog cost scenario* is similar to the standard scenario with the overtime strategy being better in stable scenarios while the chase strategy is better in higher trend and higher noise scenarios. There is a slight shift to the overtime strategy performing better as it only use inventory and backlog in extreme situations while the chase strategy continuously uses them because employees cannot be split and one employee produces multiple products each month

In the *high change cost employee scenario* the overtime strategy performs best in most demand scenarios with high noise. In medium to high noise scenarios the subcontractor quantile strategy performs the best. This can be explained by the low usage of changes in employee levels of both strategies.

In the *low overtime cost scenario* the overtime strategy performs best in all demand scenarios. This is not surprising as it already performs well in the standard cost scenario and the overtime cost has the main effect on its performance.

In the *low output scenario* the chase strategy mainly performs the best, except for high noise demand scenarios. In high noise scenarios with low to medium trend the subcontractor

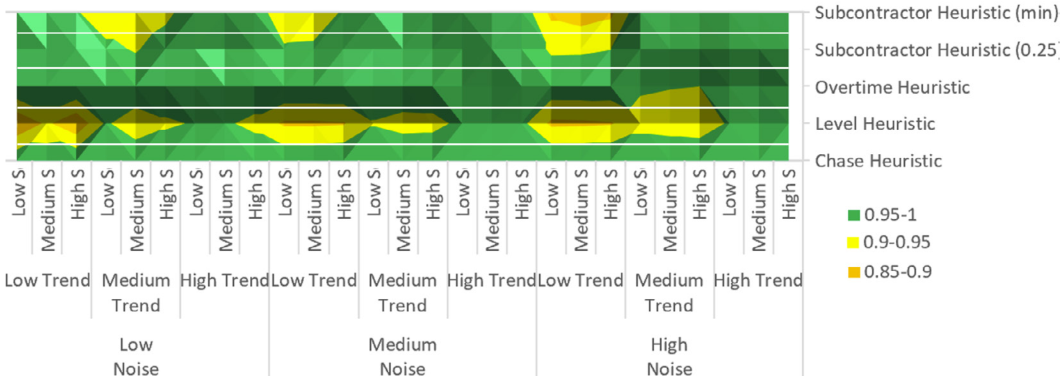

Fig. 2. Performance of the different APP strategies with standard cost factors in all demand scenarios

			chase stra.	rel. perf.	level stra.	rel. perf.	overtime stra.	rel. perf.	subcontr-quant	rel. perf.	subcontr stra.	rel. perf
Low Noise	Low Trend	Low Season	513791936	0.9894	444197832	0.8554	*519284459*	1	507908611	0.9780	506718434	0.9758
		Medium Season	507672308	0.9854	468078316	0.9086	*515150545.5*	1	503999906	0.9783	492799986	0.9566
		High Season	582441150.5	0.9954	502841286.5	0.8594	*585096365*	1	574323791.5	0.9815	558521342.5	0.9545
	Medium Trend	Low Season	821403333.5	0.9958	789872992.5	0.9576	*824789178.5*	1	796481241.5	0.9656	748325245.5	0.9072
		Medium Season	831279840	0.9979	760274525	0.9127	*832956373.5*	1	786259935	0.9439	755760289	0.9073
		High Season	*763672643*	1	717738346	0.9398	761802048	0.9975	749687901	0.9816	711720058	0.9319
	High Trend	Low Season	*1312158242*	1	1253142307	0.9550	1307196993	0.9962	1286605730	0.9805	1295790318	0.9875
		Medium Season	*1591831847*	1	1526385261	0.9588	1587049084	0.9969	1540471128	0.9677	1569221490	0.9857
		High Season	1405744235	0.9986	1314100615	0.9335	*1407674098*	1	1364364921	0.9692	1377736372	0.9787
Medium Noise	Low Trend	Low Season	509513810.5	0.9911	458771124.5	0.8924	*514048097.5*	1	491514869.5	0.9561	469276054.5	0.9129
		Medium Season	503591866.5	0.9905	453552426.5	0.8921	*508380350*	1	487161695.5	0.9582	468464737.5	0.9214
		High Season	530014602	0.9996	474967045	0.8958	*530188917.5*	1	517396184	0.9758	505997636	0.9543
	Medium Trend	Low Season	*892676393*	1	843881613	0.9453	888637251	0.9954	869611792	0.9741	872241835	0.9771
		Medium Season	*800817237.5*	1	745592162.5	0.9310	795070501.5	0.9928	777966289.5	0.9714	767826992.5	0.9588
		High Season	*798112303*	1	745105976	0.9335	791914881.5	0.9922	776645590	0.9731	771945798	0.9672
	High Trend	Low Season	*1319640423*	1	1270324229	0.9626	1290879665	0.9782	1296455855	0.9824	1302359544	0.9869
		Medium Season	*1413784532*	1	1362618010	0.9638	1384453627	0.9792	1409353038	0.9968	1404340187	0.9933
		High Season	*1616282808*	1	1558070805	0.9639	1597210059	0.9881	1589817076	0.9836	1591776351	0.9848
High Noise	Low Trend	Low Season	*463832062.5*	1	412881436.5	0.8901	456734519.5	0.9846	437231964.5	0.9426	411048090.5	0.8862
		Medium Season	*496378687*	1	442677524	0.8918	488930715	0.9849	468294170	0.9434	432845271	0.8720
		High Season	*530291090*	1	475100706	0.8959	521161486	0.9827	503196533	0.9489	470710098	0.8876
	Medium Trend	Low Season	*885178685.5*	1	823598654.5	0.9304	846985810	0.9568	874172042.5	0.9875	871292857.5	0.9843
		Medium Season	*823464591.5*	1	760438777.5	0.9234	784317705	0.9524	810949042.5	0.9848	805972109.5	0.9787
		High Season	*768651988*	1	705359622	0.9176	730375814.5	0.9502	756024813	0.9835	750938771	0.9769
	High Trend	Low Season	*1205515527*	1	1152748248	0.9562	1159418187	0.9617	1196223433	0.9922	1186892771	0.9845
		Medium Season	*1267651016*	1	1211645524	0.9558	1216321381	0.9595	1257976115	0.9923	1246375644	0.9832
		High Season	*1526709849*	1	1476163462	0.9668	1477980615	0.9680	1515235545	0.9924	1500592937	0.9828

Table 5. Profit of the different APP strategies in the standard cost scenario in the different demand cases, italic highlights best

quantile strategy performs the best, while in high noise high trend scenarios the level strategy performs the best. The better performance of the chase strategy might be explained by its better ability to match the demand if the produced goods per employee are less. The good performance of the subcontractor quantile strategy in high noise scenarios might be explained by the lower change cost of subcontractors in comparison to employees. The performance of the level strategy in high noise and high trend scenarios might be explained by two combined effects. First, the level strategy should overall perform well in high noise scenarios as it has a fast mechanism to transfer demand from one period to another making it good at high noise scenarios. Second, the subcontractor strategies perform worse with higher trends as they have to hire more and more subcontractors in between the adaption periods who work ineffectivly compared to employees.

4.3. Decision aid for APP strategy selection

Comparing the performance over all cost scenarios, the following conclusions can be drawn regarding which APP strategy to apply in real-world scenarios. The chase strategy improves with higher trends. This might result from the fact that a high trend leads to a continuous increase of the number employees, which is the strategy of the chase strategy while other strategies have to use their adaption mechanisms to cope with this. These mechanisms becomne expensive if used in great amounts or for a long time, making the performance of other strategies worsen with higher trend. Additionally, the chase strategy performs better with higher noise in some of the scenarios. This is counter intuitive and might also result from the other strategies, especially the overtime strategy, performing worse in high noise scenarios as their coping mechanisms are more expensive for high noise scenarios.

The level strategy performs better the higher the noise is, except for the high inventory cost scenario in which the noise coping mechanism of the level strategy is too costly. Additionally, in some of the scenarios the level strategy performs better with higher trends. The problem is that inaccuracies in the forecast lead to the level strategy building up inventory and backlog over the whole adaption period. With higher trends, built up backlog is used at the first half of the adaption period when the trend level is below the expected average and built up inventory is used up at the second half of the adaption period when the trend level is over the expected average level.

The overtime strategy performs worse with higher trends. This can be explained by the high overtime cost and the fact that during high trends the demand level in the second half of the adaption period is constantly higher than the expected average of the adaption period leading to a constant use of overtime. Additionally, the overtime strategy performs worse in higher noise. This can be explained as higher noise means a higher positive deviation from the average demand, which requires expensive overtime work. In lower noise and trend scenarios the performance however is very good.

The subcontractor quantile strategy and the subcontractor strategy show similar effects. Both strategies perform better with higher trend and worse with higher noise. The better performance with higher trend might be explained by the stable increase of subcontractors over time which leads to lower change costs. The worse performance with higher noise can be explained by the high subcontractor change costs that result from the matching of the demand. If compared over all scenarios, the subcontractor quantile strategy performs better than the subcontractor strategy in 35 of the 162 scenarios. This shows that in addition to the choice of the APP strategy, the fine tuning of parameters can also lead to an increased performance.

5. Summary and Outlook

Addressing soaring complexity in manufacturing, APP is a key task for which the right strategy must be selected for a given demand and manufacturing environment. With APP performance variation exceeding 5% in lost profit, selecting the right strategy is paramount; specifically, a strategy other than the chase strategy should be chosen in many cases. The results show that the analysis of the demand trend and noise level are key. A high trend tends to favor the chase strategy, a low trend the overtime strategy and a high noise level the level strategy but in a low noise level the subcontractor strategy performs best. It is apparent that to maximize performance and profit it is desirable to specifically evaluate the available APP strategies for the given environment. In future work, the auto-identification of preferred APP strategies as well the analysis of change points and contingencies leading to required adaptions should be studied. Additionally, auto-adaption and combination of basic strategies, e.g. with AI, as well as utilization of forecasting and foresighted digital twins.

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