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Effects of the update frequency of production plans on the logistical performance of production planning and control

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Abstract

The expansion of sensors located within the shop floor area drastically expands the amount of information being available for planning procedures. However, it is questionable on how far ever more current data, leading to higher production planning frequencies, are able to contribute to a higher logistical performance of production planning and control (PPC). For this purpose, we conducted a study to confront frequently described potentials of real-time abilities with adverse effects consequent to scheduling nervousness. The results of a curvilinear regression indicate that the risks of scheduling nervousness can outweigh potential benefits due to immediate schedule adjustments.

Keywords: Industrie 4.0; Digitization; Scheduling nervousness; Performance assessment; Production planning and control

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1. Introduction

Today's corporate environments are characterized by turbulent market conditions as well as growing customer demands [1]. Hence, reasonable production planning in order to meet required delivery dates becomes more and more challenging [2]. Possible relief might come in terms of technologies referring to the initiative of Industrie 4.0. Against this backdrop, a series of tools originating from the fields of information technology, virtualization as well as computing make their entry into the field of production planning and control (PPC) [3], preparing the ground for a holistic traceability of production processes [4].

A main application of real-time information in PPC is located within the tasks of scheduling processes and coordinating work orders and operations under firm time constraints [5]. In this context, real-time scheduling systems are frequently rescheduling and optimizing production plans in order to account for deviations arising from upcoming disturbances [3].

However, approaches concerned with real-time scheduling mostly neglect the pressure applied to production related processes and resources caused by frequent plan adjustments. As examined by Pujawan [6], frequent changes in the planning process can negatively affect the stability of the resulting production plans and limit factors such as staff productivity. Xie et al. [7] verified increased inventory and production costs related to frequent plan adjustments. The literature subsumes these adverse effects under the notion of scheduling nervousness. Although crucial for the performance of real-time planning, the factor of scheduling nervousness remains mainly unconsidered in current scheduling approaches. Therefore, the following study was conducted to support or falsify the hypothesis, that frequent plan adjustments of real-time scheduling approaches feature harmful consequences due to scheduling nervousness.

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2. Theoretical Framework

2.1. Digitization of Scheduling

Scheduling in the broadest sense deals with the allocation of priorities as well as the coordination of activities [8]. Referring to the tasks of PPC, scheduling is concerned with allocating job orders and their operations to machines and other resources in order to be processed [9]. The fundamental task of PPC is to optimize the job handling under limited resources [3]. The level of complexity is conditional on the scope of the considered machinery and work orders as well as the question on how to deal with dynamically occurring disturbances, such as machine breakdowns or rush orders. In this context, the concept of rescheduling deals with updating production plans, which became unfeasible due to unforeseen events [10]. In contrast to periodic rescheduling procedures, which analyze the viability of existing production plans upon expiry of a certain time interval, event-based procedures react to any upcoming disturbance and thus come closest to what can be seen as a real-time scheduling approach [11]. In order to be reactive, planning systems using event-based rescheduling algorithms are heavily depending on current information from the shop floor.

Hence, one objective of Industrie 4.0 constitutes the increased transparency of work processes within the production. One approach to achieve the desired transparency is the smartification of products and processes [12]. The term smartification describes the attachment of RFID tags or other sensors, to objects of interest, such as work orders or material [4]. The aggregation of all this sensor data allows for a real-time monitoring of objects throughout their processing, rendering an event-based rescheduling possible.

2.2. Development of the research hypothesis

Although it is obvious that the rescheduling of production plans, which became unfeasible due to unforeseen disturbances, is an important activity in efficient production planning, there is a disagreement within the research community on whether ever more frequent rescheduling is beneficial. The current research community can be subdivided into computational based research efforts, mostly laying out potential benefits of higher frequencies in rescheduling, as well as field-based research efforts, addressing respective limitations of rising rescheduling frequencies.

Following the literature concerned with computational research approaches, several authors applied simulation in order to assess the consequences originating from varying update frequencies of production plans [11, 13, 14]. Worth mentioning is especially the research conducted by Sabuncuoglu and Kizilisk [14], who simulated a reactive scheduling approach within a flexible manufacturing system. To account for a realistic representation manufacturing conditions, the simulated scheduling approach faced dynamic and stochastic environmental influences such as machine breakdowns or varying processing times. Object of investigation depicted the variation of scheduling frequencies applied, whereby the scheduling algorithm reacted to dynamic events. The simulation results showed that increased update frequencies led to a better target achievement in the form of shorter mean throughput times. Nevertheless, the research results were limited due to the fact, that no negative consequences of frequent adjustments of production plans were considered in the simulation model and that the results solely relied on simulated data.

In contrast to simulation based approaches, other research endeavors used field data in order to assess negative aspects resulting from frequent adjustments to production plans. The concepts of scheduling nervousness and instability are frequently measured variables addressing adverse effects resulting from frequent plan adjustments [6]. The instability of scheduling activities can be defined as the sum of deviations between current and new production plans. A high level of nervousness within a production originates from increasingly instable production plans [10]. As described by Blackburn et al. [15], effects of scheduling nervousness can start off at the executive level, reducing the confidence needed to successfully operate the scheduling system. Scheduling nervousness can furthermore result in direct limitations of production systems and supply chains. In this context Carlson et al. [16] were able to relate scheduling nervousness to potential problems concerned with the deployment of personnel capacity as well as planning machine loadings. Metters and Vargas [17] as well as Ho [18] substantiated redundant supplier orders, rushed sub-assemblies as well as fluctuations in the capacity utilization as results of increasingly nervous systems. Extending the theoretically based results stated above, Pujawan [6] conducted case-studies in order to further verify and assess the outcomes of scheduling nervousness. His results gave proof that a production facing scheduling nervousness can deal with a limited staff productivity as well as an increased potential for late deliveries. Although the case study approach allows for the verification of scheduling nervousness based on real world situations, the results are closely limited to the scenarios at hand.

In consequence to the so far unconnected advantages and disadvantages of increased planning frequencies, the following study asseses, whether negative effects outweigh potential benefits related to increased update frequencies. The respective hypothesis of our study is thus stated as follows:

H1: The update frequency of production plans and the logistical performance of PPC feature an inverse curvilinear relationship.

3. Empirical Study

3.1. Survey design and data collection

In order to test the hypothesis stated, the study used a hierarchical regression analysis to analyse the relation between performance measures of manufacturing companies with the update frequency of their production plans. The data basis used, stems from a survey conducted by the Laboratory for Machine Tools and Production Engineernig (WZL). The participants of the study were asked to answer the questions with regards to their own businesses. During the course of the study, 1300 potential participants were contacted twice to take part in an online survey. The 89 valid responses accounted for a response rate of 6.8 %. The majority of the participants worked in the industry sectors of mechanical and plant engineering (44.9 %), automotive (19.1 %) and electrical equipment (15.7%). More than half of the respondents worked in large companies (> 500 employees: 61.8 %) and another third in medium sized companies (> 50 employees: 29.2 %) [19]. Subsequent to the actual data collection, the dataset at hand was analyzed in terms of potential common method bias (CMB) by performing a Harman's single-factor test [20–22]. The results of the explorative factor analysis showed no single explanatory component resulting in the analysis and no single variable being responsible for the majority of the explained variance. Thus neither criterion of potential CMB applied for our dataset [23]. We furthermore analyzed our dataset regarding non-response bias, which could have been caused by characteristic differences between the groups of respondents and non-respondents [24]. Since sufficient information on the characteristics of non-respondents were missing, we followed the approach of Armstrong and Overton [24] comparing the answers of late and early respondents in order to test for a potential bias. Applying t-tests for independent samples between participants responding to the first or second survey invitation showed, that the variables concerning firm size [BI01] and revenues [BI02] might have been *exposed to a non-*response bias.

Consequently, these variables were regarded as critical during the course of the following analysis. Additional descriptive statistics, featuring correlations and respective significance levels, are listed in table 1.

Table 1. Correlation table.

	1	2	3	4	5	6	7	8	9	10	11	12
[BI01]	1											
[BI02]	.39***	1										
[BI04]	-.10	.12	1									
[BI06_01]	-.09	-.04	-.18	1								
[BI07_01]	-.09	.17	-.03	.33**	1							
[LE07_01]	-.18†	.23*	.04	-.12	.20†	1						
[PP05_05]	-.20†	-.05	.08	-.12	-.04	.20†	1					
[PP02_03]	-.26*	-.13	.11	.07	.03	.12	.03	1				
[PA14]	.01	.02	-.23*	.18†	-.07	.19†	-.07	.17	1			
[PA14_sq]	-.05	-.01	.34**	-.17	.01	-.13	.07	-.14	-.83***	1		
[LE01_s]	.07	.04	-.11	.08	.11	.12	.05	.06	.18	-.37***	1	
[LE01_c]	-.11	.01	-.02	-.04	-.14	.11	-.06	.20†	.17	-.15	.42***	1

3.2. Measurement development and assessment

The variables used throughout the following regression analysis are based on existing variables from survey-based studies on performance characteristics of manufacturing companies. Subsequent to the definition, we further assessed all the variables in terms of validity and reliability. A summary including the abbreviations and relations of the variables analyzed is given in Fig. 1.

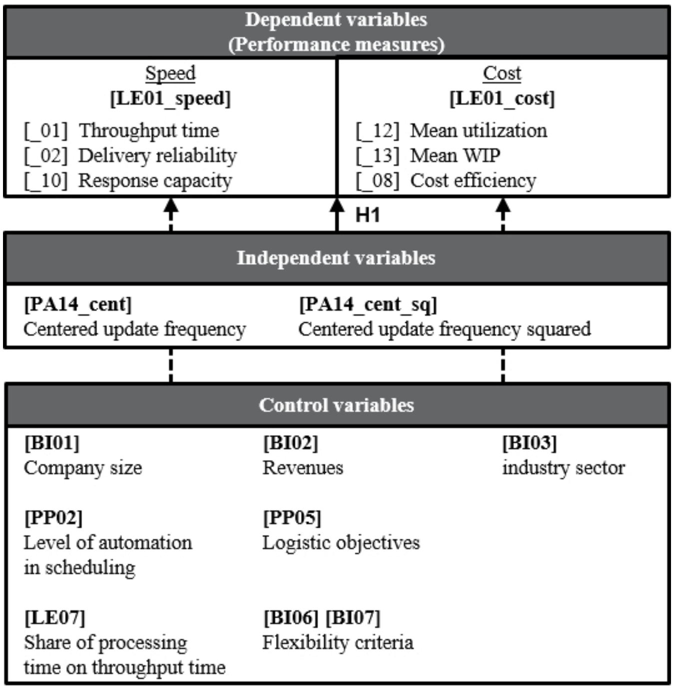

Fig. 1. regression variables.

The dependent variables applied in this survey are concerned with assessing the performance of the participating companies. Following the research approach of Tenhiälä and Helkiö [21], the performance of manufacturing companies can be assessed, inter alia, regarding the performance measures of speed and cost. We deployed a scale from Kristal et al. [25] to measure the individual performances. The survey respondents were asked to evaluate their own performance in comparison to their direct competitors, using a five-point likert scale (1: far worse; 3: about same; 5: far better). Each of the performance measures is compose of three survey items, following several suggestions of survey-based research approaches [21, 25–27]. Assessing the speed related performance measure of manufacturing companies, participants were asked to evaluate their throughput times, delivery reliabilities as well as their response capacities in case of disturbances. Assessing the cost related performance measure, participants were asked to analyze their mean work in process (WIP), utilization of resources as well as cost efficiency regarding their production. The exact survey items, the output of the exploratory and confirmatory factor analysis as well as the indicators of Cronbach's alpha (α), average variance extracted (AVE) and composite reliability (CR) are shown in table 2. Compared to common thresholds of these test statistics, the measure concerned with describing the cost related performance faces several issues of validity and reliability. The results fell below the threshold of 0.6 for Cronbach's alpha [28, 29] and 0.5 for AVE [30]. Due to the limited results of the test statistics, the dependent variables addressing cost related performance criteria were not incorporated in the further regression analysis.

Table 2. Standardized Items loading.

Standardized Items loading
"How do you rate the performance of your company in comparison to direct competitors regarding …"
Speed (CR=.78; AVE=.57; α=.605)
"… the throughput time"
"… the delivery reliability"
"… the response capacities in case of disturbances"
Cost (CR=.73; AVE=.48; α=.451)
"...mean utilization of your equipment"
"...the mean work in process"
"... the cost efficiency regarding production processes"
X^2=69.87; degrees of freedom (d.f.)=21; cmin/d.f.=3.33;

By means of the independent variables, the participants were asked to estimate the mean frequencies by which their companies make modifications to the scheduling plans. In order to estimate the update frequencies, participants either could draw on the suggested periods, such as daily or twice a day, or were able to answer in free designation. Since the objective of our study was to examine a potential inverse curvilinear relationship between the characteristics of performance and update frequency, the respective regression analysis incorporated a linear as well as squared term of the independent variable. Since collinearity was a potential threat to the results of the curvilinear regression analysis, all of our values for the independent variable were centered prior to computing the squared term needed for the further analysis [31].In order to ensure the robustness of the results, a set of control variables was included into the regression analysis [22]. These control variables complied with standardized survey items, controlling for firm size, revenue or industry sector related effects on the performance measures [21, 32]. Furthermore, more specific control variables referring to the flexibility of applied equipment and process routing, following the suggestions of Sabuncuoglu and Karabuk [33], were surveyed within our questionnaire. Finally, survey items addressing the level of automation within production planning as well as the prioritization of logistic objectives were included.

3.3. Data analysis method

Prior to testing the hypothesis, we analyzed the dataset concerning any violations of prerequisites for regression analysis. In order to ensure for the normality of the residuals accompanying our regression models, we applied the Kolmogorov and Shapiro-Wilk tests for normality following Devaraj et al. [34]. The sampling adequacy of the dataset was evaluated by applying the Kaiser-Meyer-Olkin (KMO) criterion according to Liu et al. [35]. To attest for the presence of homoscedasticity, the results of the regression analysis were analyzed applying the test statistics as suggested by Breusch-Pagan [36] and Koenker [37]. In order to address potential bias caused by co-aligned explanatory variables the regression results were tested using the variance inflated factor (VIF) (see also table 6) [38]. Finally the dataset was examined for the threat of outliers computing Cook's distance [39]. Compared to the thresholds as stated in the referenced studies, the results of the test statistics, as shown in table 3, negated potential biases within the dataset.

Table 3. Test statistics.

Test statistics	Value	Threshold
Normal distribution (residuals) [34]		
Kolmogorov	p=.2 (β=.75)	p<.05
Shaprio-Wilk	p=.398 (β=-.984)	p<.05
Sampling adequacy [35]		
Kaiser-Meyer-Olkin (KMO)	p=<.001 (KMO=.605)	p>.05
Homoscedasticity [36,37]		
Breusch-Pagan	p=.654	p<.05
Koenker	p=.421	p<.05
Multi-collinearity [38]		
Variance Inflated Factor (VIF)	VIF<4.701	VIF>10.0
Outlier detection [39]		
Cook‘s distance	$D_i<.17$	$D_i>1.0$

4. Results

The results of the regression models as well as the hypothesis were assessed regarding the coefficient of determination (R^2). The related values of R^2, adjusted R^2 as well as the change in R^2 between the hierarchical models of the regression analysis are listed in the model summary presented in table 4 and 5.

Table 4. Model summary.

Modell Summary – Regression Results				
Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	.401	.161	.005	1.00095095
2	.407	.165	-.004	1.00553803
3	.559	.312	.161	.91930442

d. Dependent Variable: LE01_speed

Table 5. Change statistics.

Modell Summary – Regression Results					
Model	R^2 change	F Change	df1	df2	Sig. F change
1	.161	1.033	13	70	.431
2	.004	.363	1	69	.549
3	.147	14.552	1	68	.000

d. Dependent Variable: LE01_speed

Table 6 shows the detailed results of the regression models, including standardized coefficients as well as the respective statistical significances and collinearity statistics.

Table 6. Regression results.

Model	Standardized Coefficients Beta	Sig.	Collinearity Statistics VIF
(Constant)		.296	
BI03_ISIC28	-.005	.973	2.117
BI03_ISIC29	.019	.900	1.836
BI03_ISIC27	-.176	.223	1.700
LE07_01	.133	.265	1.159
PP05_delivery_reliability	.415†	.083	4.645
PP05_utilization	.222	.260	3.194
PP05_WIP	.386*	.044	2.956
PP02_low_automation	-.213	.197	2.224
PP02_mean_automation	-.179	.320	2.674
PP02_high_automation	-.120	.470	2.276
PP02_full_automation	.084	.524	1.435
BI06_flexible_equipment	-.008	.952	1.365
BI07_flexible_routing	-.028	.819	1.226
(Constant)		.348	
BI03_ISIC28	-.018	.909	2.156
BI03_ISIC29	.020	.893	1.836
BI03_ISIC27	-.167	.249	1.715
LE07_01	.111	.371	1.262
PP05_delivery_reliability	.400†	.098	4.697
PP05_utilization	.207	.300	3.246
PP05_WIP	.382*	.047	2.958
PP02_low_automation	-.186	.279	2.390
PP02_mean_automation	-.172	.344	2.687
PP02_high_automation	-.122	.463	2.277
PP02_full_automation	.083	.529	1.435
BI06_flexible_equipment	-.018	.893	1.387
BI07_flexible_routing	-.012	.922	1.281
PA14_cent	.077	.549	1.341
(Constant)		.869	
BI03_ISIC28	-.077	.608	2.179
BI03_ISIC29	.036	.793	1.838
BI03_ISIC27	-.051	.708	1.808
LE07_01	.116	.310	1.262
PP05_delivery_reliability	.376†	.089	4.701
PP05_utilization	.255	.165	3.262
PP05_WIP	.348*	.049	2.966
PP02_low_automation	-.291*	.069	2.467
PP02_mean_automation	-.210	.207	2.697
PP02_high_automation	-.152	.320	2.283
PP02_full_automation	.051	.672	1.442
BI06_flexible_equipment	.015	.897	1.394
BI07_flexible_routing	-.052	.649	1.292
PA14_cent	-.546**	.008	3.977
PA14_cent_sq	-.757***	.000	3.890

Coefficients

a. Dependent Variable: LE01_speed

In the first regression model, we analyzed the influence of the control variables on the dependent variable of performance assessment. The results confirmed a positive correlation between the variables controlling for the main logistical objectives [PP05] of "delivery time" (β=.415, p<.1) and "WIP" (β=.386, p<.05) with the performance related dependent variable. The second regression model added the update frequency of production plans as an independent variable. The final regression model added the squared independent variable of update frequency to the model. As the correlation table 6 indicates, both, the linear as well as the squared, independent variables showed a highly significant influence on the dependent variable. Accordingly, the correlations suggested a negative relation between the linear (β=-.546, p<.01) as well as squared (β=-.757, p<.01) influences of increased update frequency on the performance of the PPC. Accordingly, the results support hypothesis H1, stating a curvilinear relation between the update frequency of production planning and the performance measures used.

Looking at the model summary as shown in table 4, the final regression model, including all the variables needed for the curvilinear regression, realized an adjusted R^2 value of 16.1%. The change in adjusted R^2, compared to the second regression model, amounted for 14.7%. Related survey-based studies, such as conducted by Tenhiälä and Helkio [21], achieved an adjusted R^2 of 18% with poorer values in adjusted R^2 change, arguing for the permissibility of the relation described in hypothesis 1. The graph showing the quadratic association observed in the regression analysis is illustrated in Fig. 2.

5. Discussion and implications

Our study investigated the relation between scheduling frequencies applied in the course of production planning and the implications on performance measures of the production. The findings suggest that steadily increasing the update frequencies can be harmful to the actual performance concerning speed related measures of throughput time, delivery reliability as well as response capacity. Our study thus supports suggestions from several research approaches, recommending to put a more critical view on potential threats arising from frequent changes in the production plan [6, 15–18]. During the course of the empirical based study, the performance of manufacturing companies was assessed by measuring several speed related criteria, concerning the job order handling. By confirming hypothesis stated, the regression analysis emphasized an inverse curvilinear relation between the dependent variable (performance measure) and the independent variable quantifying the update frequency (model 3 in table 3). As another result of the regression analysis, the study furthermore stressed the importance regarding logistical objectives. The variable controlling for the main logistical objective showed a significant influence on the performance criterion. Following the results of the regression analysis,

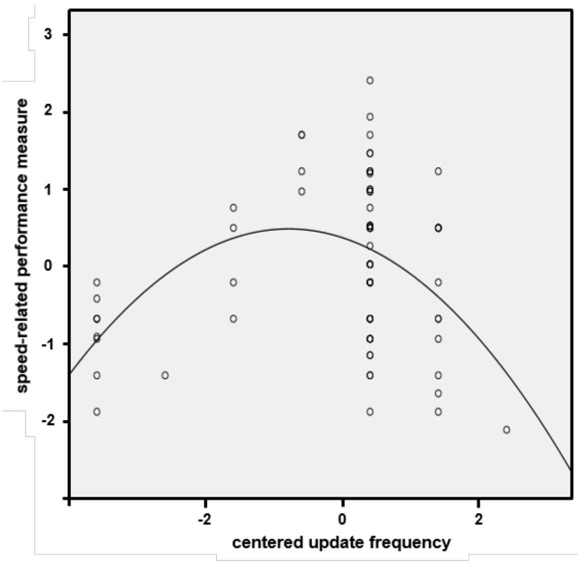

Fig. 2. graphical regression results.

companies mainly focusing on ensuring a high delivery reliability or controlling their WIP seem to outperform those companies relying on throughput times as their primary planning criterion.

The results of this study correspond with the research conducted by Pujawan [6], describing potential threats of scheduling nervousness. Additionally, the empirical study at hand offers a new perspective in terms of feasible research methods in order to investigate the scheduling issue. The survey-based approach thus sheds light on the extent to which companies may unexpectedly be suffering under a limited performance due to scheduling nervousness. The presented study furthermore depicts a linkage between current research approaches analyzing efficiencies of scheduling. Applying a regression-based approach allows for simultaneously contrasting positive as well as negative aspects related to increasing scheduling frequencies.

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