Exploring Interdependency Effects of Production Orders as Central Impact Factors of Logistics Performance in Manufacturing Systems

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Abstract. Production planning relies on accurate predictions of logistics performance indicators for production orders. Unforeseen interdependencies operational among production orders, such as unplanned prioritisation, may lead to compounding delay effects, which may negatively affect logistics performance. In this contribution, we present a general framework as well as new interdisciplinary methods for understanding production order interdependencies. We deliver first evidence of such effects in real manufacturing systems, which may lead to performance improvements when predicting logistics performance. Based on the results of this contribution, first insights into the drivers of such effects are derived.

Keywords: Interdependency effects, prediction, logistics performance

1 Introduction and Background

Predicting accurate order throughput times and due dates is a core process for manufacturers [1,2]. Conventional production planning systems in practice rely on forward/backward scheduling methods for the critical path of work orders, often using inaccurate master data. Uncertainties (e.g. quality defects, unplanned prioritization, sequence deviations, etc.) that occur during operations contribute to the inaccuracy of master data. This in turn negatively impacts the predictability of logistics performance for work orders, as those uncertainties cause unforeseeable order delays which can propagate through a production system - in other words, orders seem to influence each other over time and different machines [3–5]. Previous research has shown that some commonalities amongst order characteristics (e.g. production steps, overlap in the bill of materials, etc.) but also process parameters can be used to forecast the lateness of production orders [6]. This leads us to the main assumption of this research: so-called *interdependency effects* of orders within a certain temporal and local neighbourhood (orders for instance being processed in the same week/day and on the same and/or neighbour machines) impact logistics performance in terms of due date reliability or lead time (detailed definition see Bendul, Vican, and Hütt [7]). In the context of this research a temporal neighbourhood of orders refers to the difference in timestamps of different (jobs or) orders on particular machines; spatial neighbourhood does not refer to physical separation but rather to the common machines or workstations defined in the workplan of two or more orders. An intelligent production planning system should take into account such interdependencies in order to improve the validity of the production plan, thus improving logistics performance indicators such as average order lateness.

In a previous study, we were able to show how interdependency effects and their effect on logistics performance can be measured in manufacturing systems with a novel measurement approach based on *Granular Matter Theory* [7]. Aforementioned study shows simulative results of particularly complex discrete, job shop manufacturing environments in which – due to factors such as a highly interconnected network of machines, highly fluctuating processing times and varying work plans due to the complexity of end products – interdependencies are expected to be of significant importance. In this research, we thus aim to validate results obtained from the measurement approach for interdependencies these simulation models and prove similar effects in a real job shop production system.

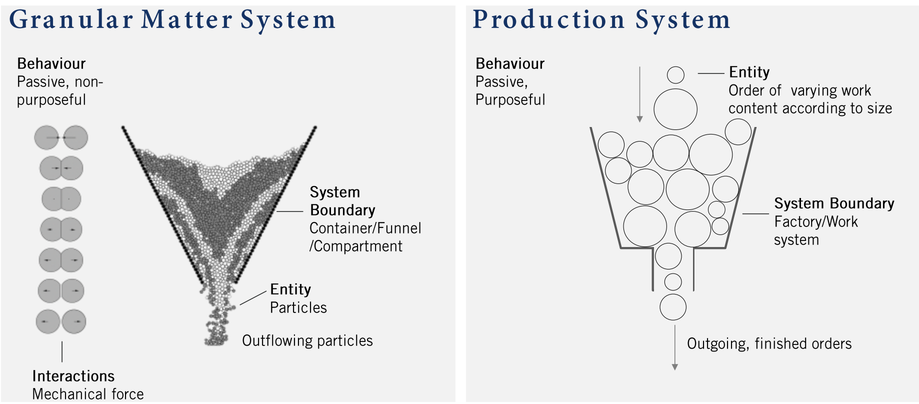
The remainder of the article is structured as follows: in section 2 we review relevant literature in production research and related fields and derive a research gap. In section 3 we introduce the research method used to investigate interdependency effects. In section 4 we present and discuss the results of the analysis. This contribution is concluded in section 5.

2 State of the Art

Interdependencies in Production Systems and the Effect on Logistics Performance: In production research, there are various studies investigating effects among production orders with varying definitions and modelling approaches. Song, Hicks, and Earl [8] investigated propagating delays among operations on subsequent machines along the work plan of components for one final product. Koh [9] simulated propagation delays between production operations for unique end products. Backus et al. [10] use a predictive model to determine order cycle times by incorporating features of production orders in close temporal proximity as predictors. Azadeh and Ziaeifar [11] predicted manufacturing lead times based characteristics of orders in the same processing sequence. Windt and Hütt [6] identify relevant drivers of order lateness in manufacturing systems and suggest that order characteristics can be used as predictors for lateness. In summary of the aforementioned studies, some of the relevant order characteristics include product types, length of work plans, job priorities, the depth and width of the Bill-of-Material, the number of processing steps, lot sizes and lot times, employee- and machine-based setup times, while logistics KPIs studied include due date deviations, order and job and throughput times. These studies suggest a relation between orders processed with similar workplans on the same machines within the same time and their delay.

Interdependency Effects in Related Disciplines - Granular Matter Theory: Interdependency effects have been studied in different research disciplines. In Physics, Granular Matter Theory was developed to model physical interactions of granular solid particles, such as sand grains. Granular matter shows specific characteristics, different from solid or liquid matters, whereby self-organized flows emerge as a result from microscopic particle-particle and particle-wall interactions. Macroscopic models, utilizing numerical particle simulations and quantitative experiments are applied to predict the self-organized flows leading to phenomena, such as convective motion causing mixing and segregation. Fig. 1 left schematically shows such a granular matter system of a large number of discrete particles in a funnel, which interact through short-distance mechanical contact within a defined system boundary. Elements with similar characteristics (highlighted in different shades of grey) "unmix" and segregate. These theoretical ideas have already been transferred to *other* research fields successfully: most notably in traffic research for example, interdependencies between cars on road were used to predict flow speeds [11]. In contrast, interdependencies are conceptually missing from one of the most established models in production research, namely Wiendahl's funnel model (Fig. 1 right), even though it closely resembles granular matter systems. In said model, inflow, outflow and characteristics of production orders have been used to explain fundamental production logistics cause-and-effect-relationships. Thus, when considering the flow of materials or production orders, interdependency effects resemble those mixing and segregation effects typically found in granular matter systems.

Fig. 1: A granular matter system (left, based on Pöschel and Schwager [12]) can be used as a proxy for a holistic framework for interdependencies in production systems (right, based on Wiendahl [13]).



Research Gap: The previous sections have highlighted studies, in which different kinds of interdependency effects have implicitly been analysed in production networks. The research gap can be summarized in the following points:

- None of the reviewed approaches from manufacturing research present a general definition of interdependency effects,
- There are only informal hypotheses or a framework regarding the effect on logistics performance.

This leads to the central hypothesis of this research: *Granular Matter Theory can be applied to production systems by modelling interdependencies among the production orders in order to predict system performance, in form of productivity, lead time or due date reliability.*

3 Materials and Methods

Application of Enrichment Analysis to production data: Observing interdependencies and resulting system behaviour between particles in granular matter systems can be achieved via direct observation in cheap and easy to replicate experimental settings. Observing interdependencies amongst production orders, however, requires physical access to multiple production companies as well as a highly intensive and long data collection phase. Basing observations on production feedback data instead circumvents a tedious data collection process, as such data contains both spatial and temporal information as well as data on many different production order characteristics for long periods of time. From the set of order characteristics, only some may be responsible for causing an interdependency. Since we hypothesize, that interdependencies are linked to differences in order lateness among different (groups of) production orders, it can be expected that only orders in a spatiotemporal neighbourhood are characterized by different patterns of order delay. Hence, a data analytic method to find interdependencies in production data needs to a) discover groups of similar data, b) assess those groups' distribution of relative lateness (i.e. the net difference between planned and actual processing time), c) show that by deleting only orders in spatiotemporal neighbourhoods, the distribution of lateness changes.

Windt and Hütt [6] presented the so-called Enrichment Analysis (EA), which closely matches those requirements. The method was adapted by Bendul, Vican, and Hütt [7] and consists of the following steps: a) cluster feedback data based on order characteristics into *k=2,3,4…50* clusters, b) compute µ enrichment via z-score of the distribution of discretized order delay in clusters, c) identify and delete orders in spatiotemporal proximity, d) repeat measurement and observe statistical difference. With respect to the method initially proposed by Windt and Hütt [6], steps c) and d) were introduced by Bendul, Vican, and Hütt [7] and represent an extension to the method, rooted in the ideas of granular matter theory. This modified EA relies on defining case-specific spatiotemporal neighbourhoods within which orders might interact. We set these parameters to the average operation throughput times (TPT) and the average number of common subsequences among all workplans.

Data description: We collected 1 calendar year of data from a job shop manufacturer anonymised as *Company B* and selected relevant order parameters as suggested by literature: BOM depth&width, set up times (operation and employee-based), lot times and sizes, transport times, setup times, location in process sequence, and number of process steps. Relative lateness was calculated for all operations as the net total difference between planned and actual processing time. A preliminary analysis of value distributions has shown some outlier values exceeding +- 100 for operation setup times, employee-based setup times, transport times, planned operation times, throughput times and lateness.

Table 1. Description of *Company B* data set

# Orders	# Operations	*Order* TPT (days) CV[a] Plan	*Order* TPT (days) CV[a] Act.	*Operation* TPT (days) CV[a] Plan	*Operation* TPT (days) CV[a] Act.	Avg. workplan length (# machines)
18,294	100,313	1.00	1.24	1.25	3.27	5.48

[a] Coefficient of Variation

Those orders were deleted. Furthermore, negative values of -100 for all parameters except lateness were deleted. Data was centred and scaled before applying an unweighted k-means++ algorithm. As Table 1 shows, after pre-processing there are 18,294 orders with 100,313 operations used in the analysis, leading to an average of 5,48 operations for each order and the stated average throughput times (and variation).

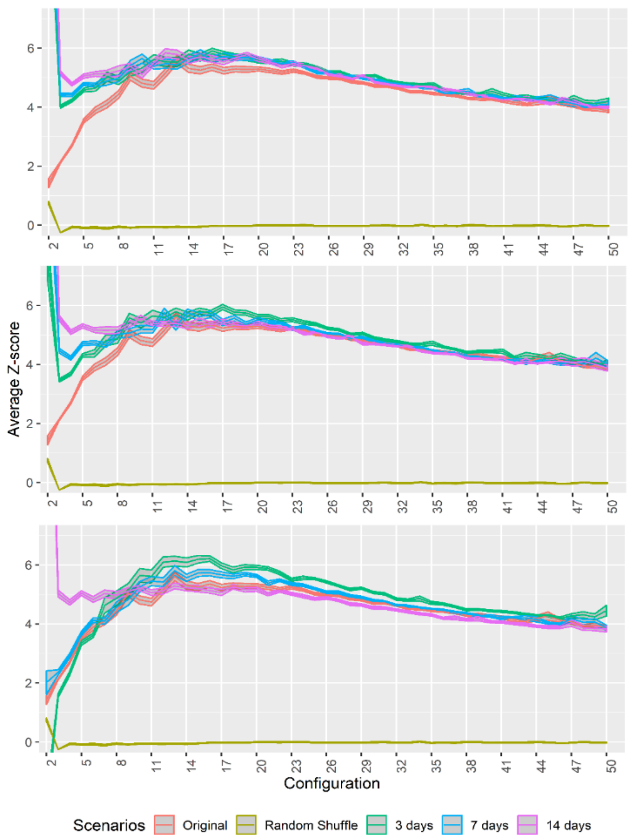
Setting an appropriate neighbourhood size within which orders might interact should follow some general assumptions: 1) Set temporal neighbourhood size to at least the average operation, (alternatively order) throughput time – a preliminary analysis of the operation and order throughput times is required, 2) set spatial neighbourhood size to the average number of common subsequences among all workplans – again, a preliminary iterative analysis can be used on a case by case basis. We set a time horizon for the temporal search space to three, seven, and fourteen calendar days and a temporal search space to one, two, and three machines. Since the exact temporal neighbourhood at which the strongest interdependency signal is observed cannot be determined prior to executing the algorithm, these values provide approximations to narrow down the expected range of observation.

4 Results and Discussion

Interpreting the results: The EA yields Fig. 2, where each graph shows the *k*-number of clusters production data was clustered into on the x-axis. The y-axis shows the average enrichment of lateness in the respective configuration. Each series denotes a temporal neighbourhood within which orders were deleted. Additionally, the red series shows the mean enrichment for clusters of production data, where no orders were deleted, thus serving as the baseline. Each individual of the three graphs used a different spatial neighbourhood of 1-3 machines top to bottom. Observing a difference in the peak enrichment from the baseline to any scenario where data in spatio-temporal neighbourhoods (i.e. where orders share the same machines on their workplans with operations scheduled during the respective time window) were deleted implies the presence of interdependencies.

Are there interdependencies between production orders in real data? The most distinct separation from the baseline curve can be observed at a temporal neighbourhood of *three days* and spatial neighbourhood of *three common machines* (green, bottom). This roughly corresponds to the average operation TPT of 3.46 days and about half the mean workplan length. Increasing the temporal search space up to fourteen days yields no meaningful clustering configuration greater than $k = 2$ and hence no interdependency effects, comparable to a scenario where production orders and their lateness were shuffled randomly. The results of the analysis suggest that production orders interdepend in certain, case-dependent spatiotemporal neighbourhoods. Furthermore, these results affirm previous insights from studies in simulated job shops with comparable results by Bendul, Vican, and Hütt [7].

Fig. 2.: Results of the enrichment analysis for *Company B* indicate interdependency effects between production orders for a spatiotemporal neighbourhood of three days and three common machines



5 Conclusion and Outlook

The analysis presented in this contribution has shown that the novel data analytical approach can be applied for discovering interdependencies in real production data. We were able to show how different search spaces affect the emergence of interdependencies and validate previous simulation results. The results of the analysis primarily indicated that orders which share similar machines on their workplans and are scheduled for similar times show an increased potential for mutual increases in relative lateness (i.e. total deviation from planned to actual processing times). As is common practice, increases in total processing times for orders are often compensated by increasing the master data used in production planning without further analysis. While the root of these interdependencies are complex and subject to further analyses from additional operational data, immediate lessons learned from this analysis in combination with previous research confirms that avoiding overlapping production schedules for certain production orders may avoid unnecessary delays without making major changes to workplans or increasing the master data used in production planning.

The results also provide an indication for the gap in hypotheses regarding the relationship between production order interdependencies and the effect on logistics performance: there appears to be a negative impact on logistics performance with a higher overlap of orders in spatiotemporal neighbourhoods. Formalising and testing this hypothesis is subject of further research.

EA is a statistical analysis and therefore to determine true causal relationships, simulation experiments need to be conducted, specifically also test for the impact of certain factors: Does the strength vary with the amount of spatiotemporal overlap? What role do structural properties of the material flow network among machines play? Does the variability in throughput times play a role? Further work should also include analysing a broader range of real company datasets to further validate the approach presented.

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