

Is there empirical evidence on non-linear relationship between lead time and resource utilization in manufacturing processes?

Yvan Nieto¹, Dominik Gläßer², Gerald Reiner³

¹ Institut de l'entreprise, Université de Neuchâtel - Rue A.-L. Breguet 1
CH-2000 Neuchâtel, Switzerland

E-mail: yvan.nieto@unine.ch, telephone: +41 32 7181360

² Institut de l'entreprise, Université de Neuchâtel - Rue A.-L. Breguet 1
CH-2000 Neuchâtel, Switzerland

E-mail: dominik.glasser@unine.ch, telephone: +41 32 7181360

³ Institut de l'entreprise, Université de Neuchâtel - Rue A.-L. Breguet 1
CH-2000 Neuchâtel, Switzerland

E-mail: gerald.reiner@unine.ch, telephone: +41 32 7181360

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Abstract

The trade-off between resource utilization and lead time in make-to-order systems is among the most recognized insights gained from queuing theory in production management. However, even if there are not doubts related to axiomatic quantitative research, the exponential relationship between lead time and utilization has not been explicitly investigated based on empirical data in the context of complex manufacturing processes. There are several reasons for this gap, e.g., implicit efforts made by companies to overcome lead time increase in heavy workload situations.

To pursue the research question empirically, we selected a company for our study that is an international leader in producing polymer solutions. This industry is characterized by challenging customer requirements, in particular short lead times and high level of responsiveness with high quality. We consider about 19,000 different products for a period of three years and scrutinize the nature of the relationship between lead time and resource

utilization. The findings highlight the complex behavior of lead time regarding utilization and show that this relationship can not be explain using simple queuing models alone.

Key words: Empirical Research, Lead time, Utilization, Queuing theory.

1) Introduction

Identified as a source of competitive advantage for companies since more than 20 years (Stalk, 1988), time remains nowadays of strategic importance for most companies. On the one hand, short lead times are required to fulfil customer expectations. On the other hand, long lead times generate increased costs due to higher work in process and safety stocks (Hopp and Spearman, 2000). This opportunity of leverage on both customer satisfaction (i.e. effectiveness) and costs (i.e. efficiency) draws much interest in industry. Nevertheless, many managers fail in understanding the complex system dynamics of lead time reduction (De Treville et al, 2009). To them, lead time reduction still means working faster, harder and longer in order to complete the job in less time, missing at the same the functional dependencies between lead times, capacity utilization and variability (Suri, 1998). A reason for that is that the mathematical principles that drive lead time are counterintuitive and go against standard management training that emphasizes increasing resource utilization (De Treville and Van Ackere, 2006).

Queuing theory provides the theoretical foundations for lead time reduction. Comprehensive mathematical descriptions of the links existing between the involved factors (e.g. utilization, variability ...) can be found in Hopp and Spearman (2000). Among these relationships, the trade-off between resource utilization and lead time in make-to-order systems is among the most recognized insights gained from queuing theory in production management. Utilization should be understood as the percentage of time a work centre is occupied in production or production related activities such as e.g. run time, setup, maintenance, etc. Also, the average

lead time can be defined as the sum of the average waiting time and the average processing time. Suri (1998) showed that the waiting time component is associated to an increasing effect related to utilization, which leads to an exponential relation between resource utilization and average lead time. Even the magnifying effect is restricted to the waiting time, this is sufficient to shape the entire relation as it was shown that waiting time constitutes in average 85% of the total flow time (Tatsiopoulos and Kingsman, 1983). The exponential relationship between resource utilization and average lead time is illustrated in figure 1.

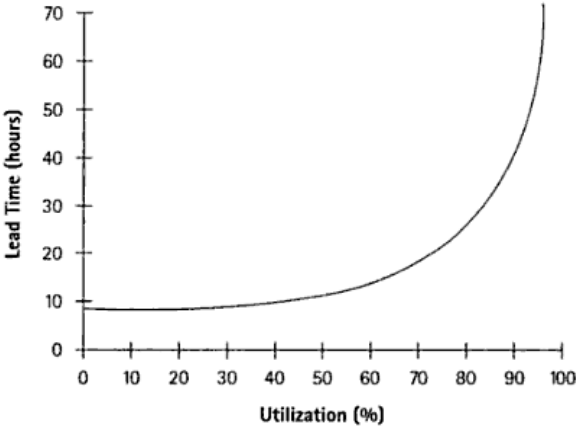


Figure 1: Lead time as exponential function of utilization (Suri, 1998).

However, despite the strength of this axiomatic quantitative finding, numerous pitfalls exist when transferring this knowledge to practice. In the fast changing environment faced by most companies, the assumption related to queuing theory, in particular constant arrival patterns and steady-state behavior may not be respected (Govil and Fu, 1999). For instance, variability in the arrival rate (e.g. variability in demand due to external economic factors) and processing time may impede the system to reach steady state. The effect of variability is well known as well and has been depicted by Suri (1998) as presented in figure 2.

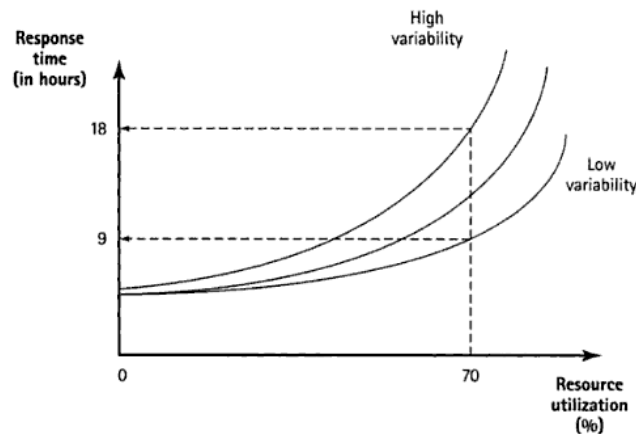


Figure 2: Dependencies between utilization, lead time and variability (Suri, 1998).

However, despite the importance of queuing theory in manufacturing processes, very few empirical researches investigate the nature of the relationship between lead time and utilization (Pahl, 2005). Empirical knowledge in the context of complex manufacturing processes is necessary in order to better understand lead time dynamics and identify the gap between existing model and company practices. Indeed, in order to avoid the negative consequences of large lead times, companies may apply hedging practices (e.g. postponed maintenance activities, short term incentive to work faster/longer,...) to overcome lead time increase in heavy workload situations. Such practices will impact the lead time distribution, blurring at the same time the possibility to observe the theoretical relationship between utilization and lead time. That lead to a fundamental problem, i.e., even when being aware about these theoretical relationship, managers are not able to observe it in reality. Due to the fact that they are fighting all the time with hedging practices against the symptoms instead of dealing with the causes.

In this study we consider the dynamics of the lead time regarding resource utilization from an empirical point of view. We opted for case study methodology as it is known to allow for theory testing (Voss, 2009). The selected company for our study is an international leader in producing polymer solutions. This industry is characterized by challenging customer

requirements, in particular short lead times and high level of responsiveness with high quality. We consider about 19,000 different products for a period of three years and scrutinize the nature of the relationship between lead time and resource utilization. Based on interviews with production and supply chain managers, we also identified internal company practices and external environmental circumstances influencing lead time.

The paper is structured as follows. In section 2, we present the case studied in this paper, focusing on process management and data collection. In section 3, we develop the analyses performed and expose the results. Finally, we provide in section 4 a discussion, including implications for both academics and practitioners. Also, some insights for further research are given.

2) Case Description

We studied the manufacturing processes of a large multinational production facility of a world leading polymer processing company. We opt for this facility, because it has to act within an agile supply chain environment which means that lead time plays a decisive role (Naylor et al., 1999; Christopher and Towill, 2000; Mason-Jones et al., 2000). Moreover, the manufacturer produces 24 hours and 365 days a year. These are perfection conditions for our analysis, because no queues are built during e.g. weekends. Furthermore, one of the management principles is to keep the capacity utilization at a very high level to achieve cost advantages.

In the following paragraphs, we will first present the organizational structure of the production facility, describing the order fulfillment process from customer orders reception to finished products shipment. Second, we will specify the data utilized to investigate the relationship between utilization and average lead time at this particular plant.

Company organization and order fulfillment process

Customers from all over the world are assigned to one of the 38 sales offices. Each sales office is responsible for the customer relationship management including taking customer orders by phone or over a defined electronically interface, price negotiations, etc. Furthermore, huge sales offices are also accountable for maintaining the corresponding warehouse.

If a customer order is received, they check it for completeness and directly transfer it to the manufacturer. Another possibility is that the reorder point for finished goods on stock is reached and an inventory replenishment order is send to the manufacturer. Based on the customer due date which is normally in the near future the production orders are allocated to resources. Finished products are transferred to the internal finished goods inventory (make-to-stock) or are delivered directly to the customer respectively to the sales office's inventory (make-to-order). The whole process is depicted in figure 3.

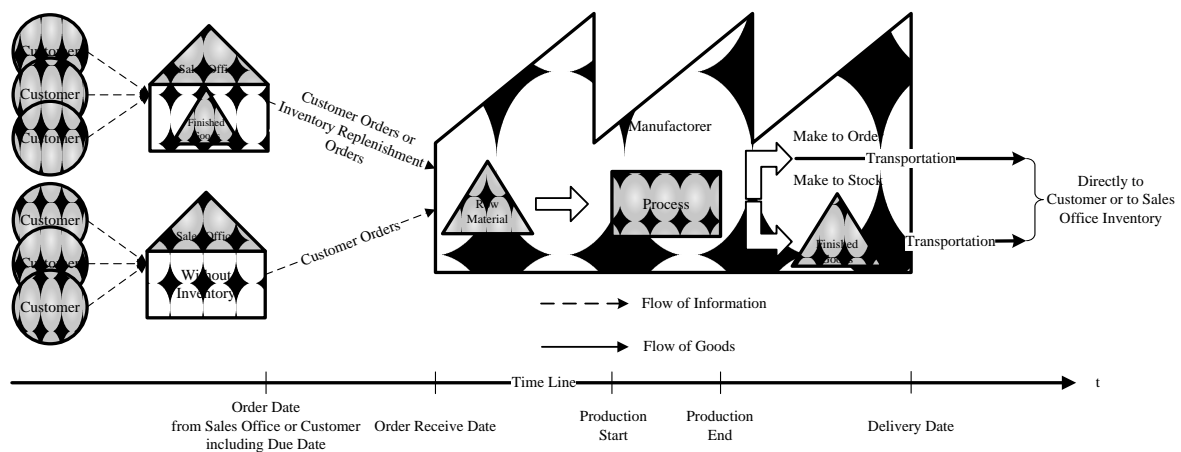


Figure 3: Process layout including time line.

Data collection and validity

In order to obtain data free of organizational barriers and to validate the data, a data triangulation approach was chosen (Croom, 2009). On the one hand, we used existing data

from the IT system. On the second hand, we conducted unstructured interviews (Voss, 2009) with key users, e.g. supply chain manager, production manager and IT manager.

Data collection was carried out for the entire production facility for a period of three years. We received over 60.000 production orders whereof more than 16.000 are make to order. For every production order there is the customer/sales office due date, customer/sales office order date, delivery date to the manufacturer, production start date, production end date, delivery date to the customer/sales office, order quantity and article information included. See the time line from figure 3 for a better understanding of the different time stamps a production order is containing.

Besides the time stamps of the production orders for assessing the lead time, the information about resource utilization is necessary. In order to gain the capacity utilization for the 45 machines, we evaluated 50 different time codes for every single machine. It is documented when there is a change exactly to the second which is equal to 600000 data sets.

3) Data analysis and results

To investigate empirically the nature of the relation between lead time and resource utilization, we first evaluated the average daily utilization of each machines of the facility. Several ways to compute utilization are possible regarding the definition considered for utilization. In this study, we followed the definition from Suri (1998) and therefore, we assign each machine activity period to one of the following categories: “unavailable”, “occupied” or “idle”. Unavailable periods are periods when machines are not allowed to produce as during public holiday. Occupied periods group all the production activities such as setup time, breakdowns and running time, including maintenance and raw material shortage. Finally, “Idle” periods are periods when machines could produce, but no production is required, i.e. shortage of orders.

Based on the IT information monitoring machines activity exactly to the second, we calculated the average utilization by dividing the sum of the “occupied” periods by the sum of the available periods (i.e. 1 - sum of “unavailable periods”). This evaluation was performed on a daily basis. The daily average utilization of the plant was obtained by averaging the utilization of each of the 45 machines. Figure 4 shows the evolution of the average daily utilization of the plant from January 2007 to December 2009. Interviewed managers agreed that the increased variability exhibited in 2009 resulted from the global finance crisis.

Second, we assessed the order lead time by evaluating the time elapsing from order reception to the order end of production. The analysis considered 16,584 orders that involved a strict make-to-order process. Delivery time has been omitted from the lead time to avoid additional variability related to external third party logistic service providers. Also, plant holiday time where removed for lead time computation.

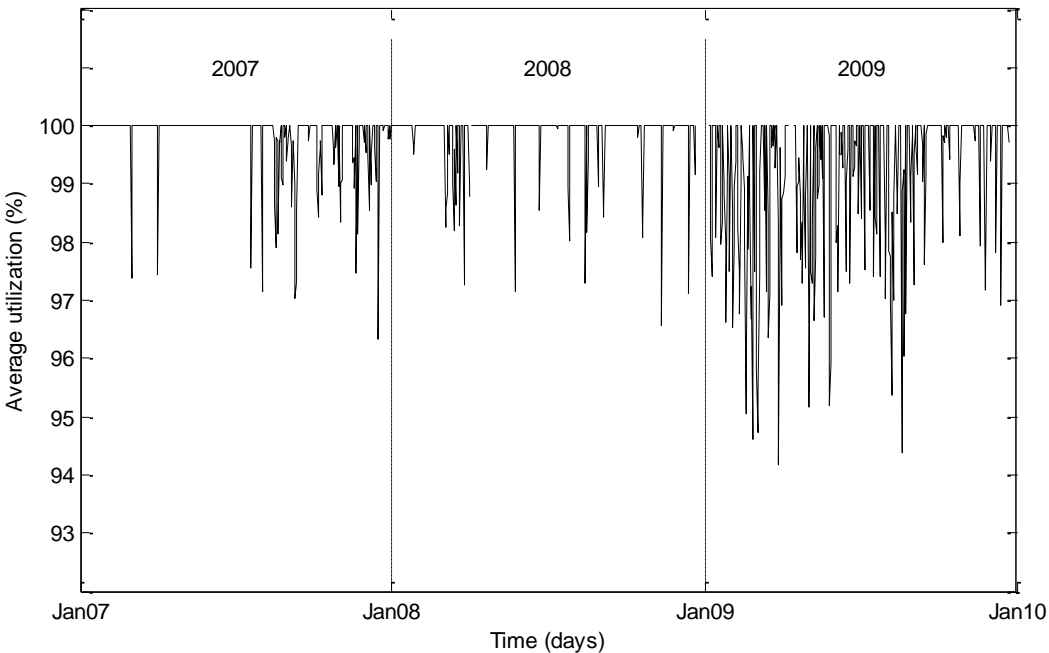


Figure 4: Evolution of the average daily utilization of the plant

Finally, we assessed the utilization during lead time by averaging the daily average utilization of the plant associated with each order lead time period. Figure 5 presents the scatter plot of the 16,584 orders lead time obtained versus their relative average plant utilization during lead time.

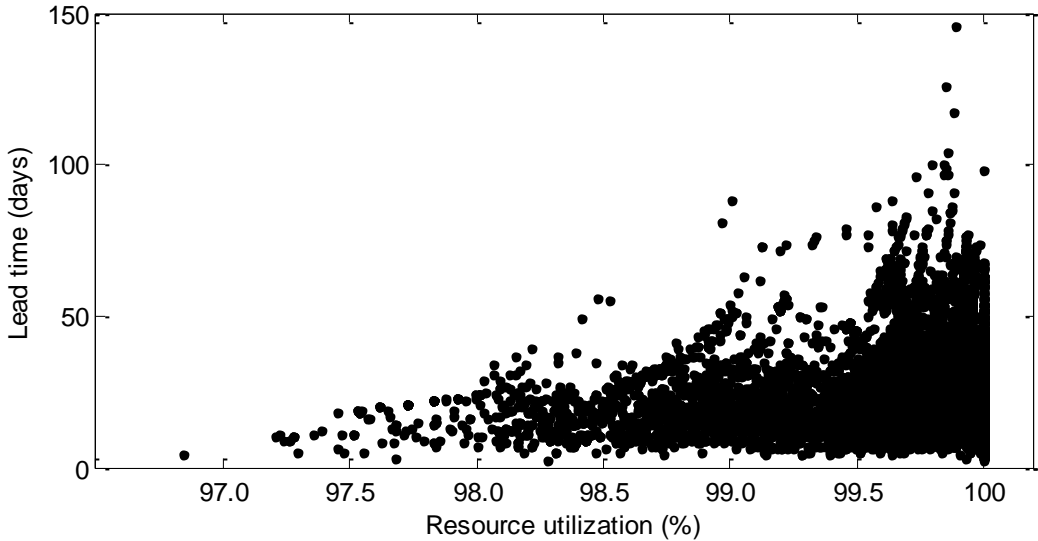


Figure 5: Relationship between lead time and utilization

Based on figure 5, several remarks need to be commented. It is clear that the expected relationship is not obvious in figure 5. The presence of numerous orders with short lead times even utilization is extremely high indicates that the queuing model does not fully hold in our setting. Of course, this is only partially true, as queuing theory is considering average lead time and not individual order lead times. However, analyzing the average lead time per level of utilization (i.e. grouped in utilization categories of 0.5%), no significant growing trend could be identified. Despite the lack of general relationship, it seems that an exponential behavior of the lead time regarding utilization is not completely absent in figure 6. Rather than none, it seems that several exponential curves are included in figure 5, remembering to

some extend the pattern presented in figure 2. This consideration would imply a blurring effect induced by some sources of variability.

After discussion with company managers, the main factors influencing order lead time were identified as demand and backlog levels. Based on this conclusion, we partitioned our dataset in clusters based first, on the demand level over the 3 weeks following the order reception (i.e. the length of the average lead time for the orders considered), and second, on the level of the order backlog on the order reception date (i.e. the number of products units pending to be proceeded). We identified 9 clusters based on k-means clustering method and partitions were performed based on squared Euclidean distances (Seber, 1984). Figure 6 presents an illustration of two of the resulting clusters, respectively with high demand and high backlog (figure 6, a) and with low demand and low backlog (figure 6, b).

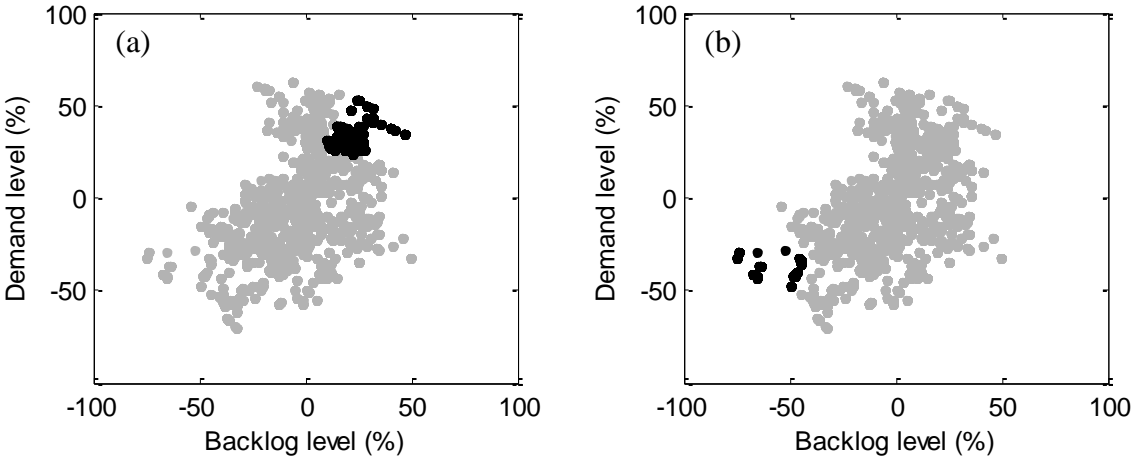


Figure 6: Illustration of the repartition of the demand and backlog related to each order (in gray). (a) Black dots highlight the cases belonging to the example of cluster with high demand and high backlog. (b) Black dots highlight the cases belonging to the example of cluster with low demand and low backlog.

Building on figure 5, figure 7 presents the repartition of the cases belonging respectively to each of the example clusters. It can be observed that in the case of high demand and high backlog cluster (figure 7, a) the exponential relationship is obvious. However, this is not the

case for the second cluster (figure 7, b). As a consequence, it seems that the variability of the demand and of the backlog, as captured in the way presented above, is only a part of the factors influencing the relation between average lead time and resource utilization. According to that, further discussions were lead with the company managers, in order to identify further potential factors of influence. Preliminary results of this analysis are presented in the remaining part of this section.

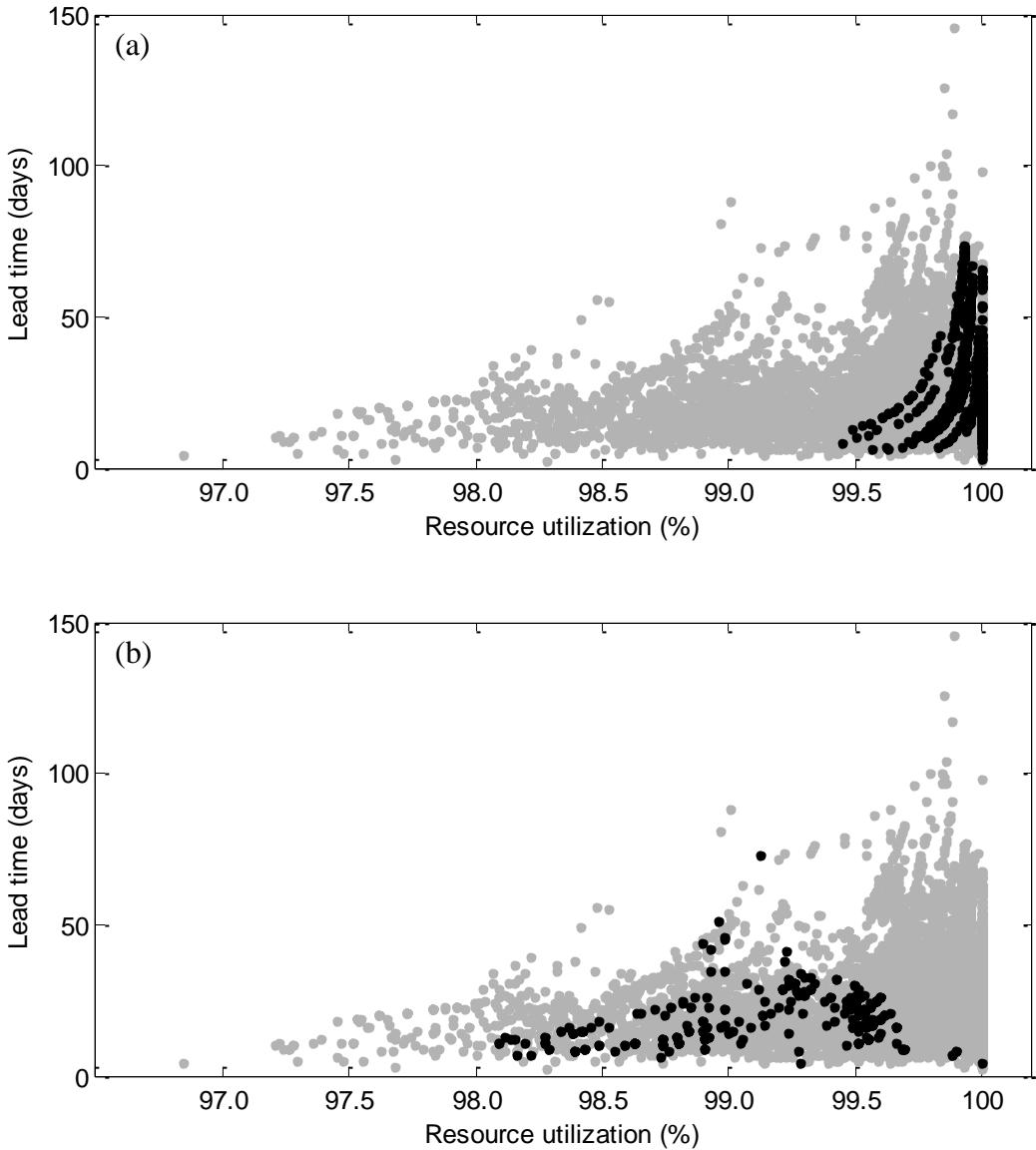


Figure 7: Plots a (high demand and long queue) and b (low demand and short queue) show the relationship between lead time and utilization for different conditions

Cause and Effect analysis

Based on the discussions with company managers, numerous potential factors of influence were identified. A synthesis of these factors is presented in figure 8 in the form of a cause and effect diagram. Moreover, in order to enrich the list of potential influences, we performed a preliminary literature research on this topic. Several contributions have been identified from this additional step as for instance in Vaughan (2004), Karmarkar (1987), Suri (1998), Askenazy et al. (2006), Silver et al. (1998), Nahmias (2005), Beamon (1999).

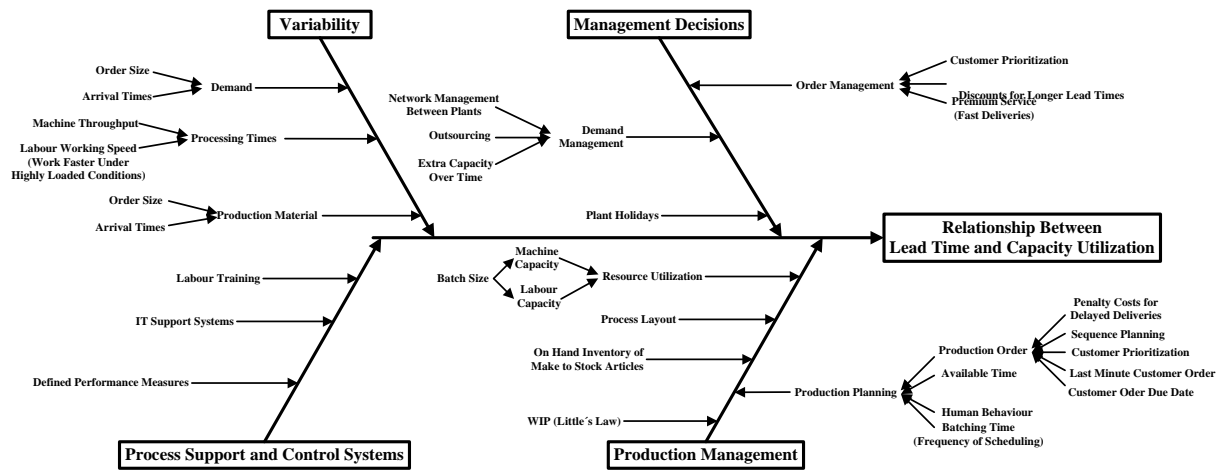


Figure 8: Ishikawa diagram of the influencing variables on the relationship between lead time and capacity utilization.

We believe that some of these factors might explain the lack of clear general relationship between average lead time and utilization. Further work is required in order to assess the impact of these factors on the relationship and support better understanding of the nature of this relationship in empirical settings.

4) Discussion

In this study, we empirically investigate the relationship between average lead time and resource utilization. We evaluated the order lead times of more than 16.000 orders as well as their respective average resource utilization during lead time. Based on these measures, we were able to evaluate the nature of the lead time-utilization relationship. Results showed that there is empirical evidence on non-linear relationship between lead time and resource utilization. This highlights potential danger in maximizing utilization in this particular process.

However, this relationship is not as obvious as assumed by the simple queuing theory model presented in the introduction. Our study shows the strong impact of variability, i.e. measured as demand and backlog variability. These findings are in line with theory. Moreover, the results show that further influencing factors, i.e. additional to demand and backlog variability, are involved shaping the relationship between average lead time and utilization. As a consequence, further research is needed in order to assess the impact of these additional factors and support better understanding of the nature of this relationship in empirical settings. This statement supports the call from Govil and Fu (1999) for more sophisticated queuing models, i.e. able to better integrate the complexity of real manufacturing processes.

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