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Using Monte Carlo Simulations and Little's Law to Improve Process Planning

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Abstract

Production planning and scheduling are challenging with recent disruptions in the supply chain and increased demand for reduced lead times. With an increased demand for production and ever-changing delivery dates of raw materials, a dynamic production planning model with machine-operator-part-specific historical data is essential for small and medium-scale manufacturers. Based on the sales orders and inventory, machine production rates, and work-in-process information, Little's law estimates the initial lead time. To improve the accuracy of the lead time, a Monte Carlo simulation based on the historical data of the machine-operator-part production rate is used along with the queuing principles and theory of constraints. The theory of constraints is used to facilitate issues such as preventive maintenance, unscheduled machine breakdown, etc. The dynamic nature of the shop floor issues is used to update the Monte Carlo simulations to improve the process flow and the lead time estimation. This model was implemented as a case study at a cutting tool manufacturing plant to reduce lead time and increase customer satisfaction. Finally, the paper reports the case study's findings to estimate the lead time effectively and facilitate the production planning and scheduling process. Overall, the results showed that the model has assisted in reducing the lead times and backorders, proving the present study's hypothesis. Using Little's law and Monte Carlo simulation using real-time data has enabled an accurate estimate of the lead time and improved customer satisfaction.

Keywords

Monte Carlo; Little's Law; Process Planning; Scheduling; Queueing Theory

1. Introduction and background

The manufacturing industry's global revenue is more than 10 trillion U.S. dollars and is projected to grow in the next few years as worldwide consumption and demand keep growing [1]. Manufacturing industries face external factors, such as market fluctuations, social/political, environmental, etc., and internal factors, such as machine issues, human resources, new machine installation, etc., that influence the on-time production and delivery to the customer [2]. One of the key components of successfully delivering the manufactured component to the customer is production planning, scheduling, and processing the part to the specification[3]. However, production planning and scheduling have been challenging with recent disruptions in the supply chain and increased demand for reduced lead times. A dynamic production planning model with machine-operator-part-specific historical data is essential for small and medium-scale manufacturers to overcome challenges like ever-changing delivery dates, machine failure, employee absence, etc. [2], [4]. Researchers have been using Monte Carlo simulations to estimate the delivery dates and plan the machining maintenance schedule, machine upgrades, etc. [4], [5]. Franke et al. have used the Monte Carlo simulation for production planning in a textile industry using historical data and the uncertainties of the general production environment [4]. Bakir et al. developed a multi-stage Monte Carlo method to optimize the production planning at a paint process plant [6]. In the manufacturing industry, Monte

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Carlo simulations are used for production planning forecasting [7] and process optimization [8]. Li et al. used a metal model as an input for the initial estimates for the production planning and later used the Monte Carlo Simulations for estimating the delivery dates [5].

Litte's law is a simple mathematical model used in multiple fields (supply chain, manufacturing process planning, etc.) that provides the initial estimates of the work in the process needed based on the process throughput and the lead time needed based on the sale orders and the inventory levels. Little's law $L = \lambda w$, where L is the work in progress, λ is the average lead time, and w is the run rate [9]. Monte Carlo simulations are a mathematical tool that provides possible outcomes based on the probability of different process uncertainties and interdependent input parameters. The uncertainties include machine downtime, human resource issues, new product development, etc., while the interdependent input parameters include machine run rate, sale orders, inventory, etc. The Monte Carlo simulations provide an estimate with confidence intervals, depending on the number of simulations run and the input parameters [4]. This paper used Little's law to estimate the initial lead time for production planning based on sales orders and inventory, machine production rates, and work-in-process information. Later, to improve the accuracy of the lead time, a Monte Carlo simulation based on the historical data of the machine-operator-part production rate is used along with the queuing principles and theory of constraints. This paper presents the result of implementing the combination of Little's law and Monte Carlo simulation to estimate the lead time and production planning at a small to medium-sized cutting tool factory.

By mid-2021, the global supply chain's stability had rapidly declined due to the disruptions from COVID-19, changing the import/export balance of the world's economy. Many manufacturers faced challenges sourcing raw materials, machinery, tools, and staffing. This combination led to missed promised order dates, incomplete shipping of orders, commitment to more resources to expedite shipments, and prioritization of customers over others. To address declining customer satisfaction, a model was developed using Little's law and Monte Carlo simulations to improve production planning, backorder reduction, and the current scheduling process. Implementing Little's law allows us to estimate lead times in our trial manufacturing process. Lead time and customer demand averages are combined with standard deviations and their coefficient of variance to capture the effects of unstable processes, fluctuating customer demand, and other uncertainties. The Monte Carlo simulations use the initial estimate from Little's law at 20,000 iterations to estimate the time to finish making the part (lead time for the customers). Each manufacturing process contributes its unique production set and work-in-process data inputs. Analysis of the Monte Carlo simulation outputs enabled us to define lead time probabilities until the desired probability of success was reached. The results are then used to calculate the lead time of any individual stock keeping unit (SKU) based on its progress within the value stream. Using a goal of a higher probability of success, some customer orders were being filled earlier than the projected fulfillment date. Improvements in the lead time and backorders were measured to gauge the success of this model and address any needed adjustments. Overall, this paper presents a model to improve the accuracy of the lead time prediction by combining the Monte Carlo simulation based on the historical data of the machine-operator-part production rate and queuing principles.

2. Methodology

Using Little's law and Monte Carlo simulation data became a real-time representation of our manufacturing processes, enabling more accurate production scheduling and updates to shipment dates as needed. The model developed provided an optimum production trigger, batch sizes, and safety stock levels. Lead time and demand variations were crucial in determining satisfactory reorder points and quantities. These are updated monthly with annual demand and current lead time inputs. In this context, safety stock is defined as the amount of inventory required to meet demand during the current lead time. This creates the first signal to production that expediting is required. Continuous improvement practices, such as visual management, setup reductions, 5S methodology, and layout rationalization, can be applied to further decrease lead times. When data revealed a buildup of work in process, we began to utilize the theory of constraints, adapting to the previously unknown bottleneck. Each SKU was assigned a detailed path through the process resources, established by considering the largest set-up adjustment factors and minimizing them across the process flow. We chose to target set-up adjustments because they can consist of 50% of the total set-up time. A pull system was utilized to constrain the previous production process to the bottleneck. This system was incorporated into the schedule, producing production triggers only when the bottleneck was manageable. Continuous data collection and analysis identifies opportunities for improvement. The effect of these improvements can be seen in reduced work-in-process and quantity of finished goods. Longer lead times lead to larger inventory requirements, while short lead times reduce inventory needs.

Process flow for the Little's law and Monte Carlo simulation methodology:

1. Throughput and work in process levels are recorded for the previous 45 days.
   a. The average and standard deviations of this data are calculated.
   b. Using Little's Law, the lead time of the process(es) is estimated.
      Average lead time $\lambda = L/w$
      Standard deviation of lead time σ_l

2. The Little's Law lead time output (λ), customer demand trends, standard deviations (σ_l), and the coefficient of variance ($CV = \sigma_l/\lambda$) of the data sets are used to determine finished inventory, reorder point, and reorder quantities requirements.
   a. Inventory requirements adjust relative to the process inputs and customer demand trends.
   b. Production batch sizes become optimized to satisfy demand expectations.

3. Inventory and work-in-progress data are used to calculate the SKU's inventory position.
   a. The inventory position is the sum of finished goods inventory and work in process minus any rework inventory and known customer orders.
   b. Only known customer orders with a due date within the lead time are considered.

4. Production needs are communicated to manufacturing with an expectation of first in, first out flow.
   a. Communication occurs at the operator level whenever possible to reduce the need for management intervention and the resulting variation.
   b. Expediting needs are determined by backorders and future orders within the process lead time.

5. Little's Law lead time output and the lead time variation data become the input parameters for the Monte Carlo simulation.
   a. Variation data includes employee absence, machine breakdowns, production setups, expediting, and all other flow disruptions: based on this information, the products are separated into four quartiles, say Q1, Q2, Q3, and Q4. A lower standard deviation multiplier S_m is used for high-demand products and situations with lesser constraints (mentioned above), while for lower-demand products and situations with higher constraints, a higher standard deviation multiplier is used, as shown below. The increase in the multiplier increases lead time variation, uncertainty, and cost of the goods.

If $CV < Q_1$

$S_m = CV/Q_1$

else

if $(CV \geq Q_1 \; or \; CV < Q_2)$

$S_m = \frac{CV}{Q_2} + 1$

else

if $(CV \geq Q_2 \; or \; CV < Q_3)$

$S_m = \frac{CV}{Q_3} + 2$

else

if $(CV \geq Q_3)$

$$S_m = \frac{CV}{Q_3} + 3$$

6. Using the standard deviation multiplier (S_m), the Monte Carlo simulation is run 20,000 times.
    a. Results are compiled as a 100% customer order fill rate probability.
    b. Strategic risk assessment by company management determines the acceptable probability result.
7. The resulting lead time is communicated to the customer for order due date expectations.

    a. With the dynamic nature of the model's inputs, if process variation changes the manufacturing lead time, this can be communicated to the customer as needed.

3. Results and discussion

To implement this methodology, the hole saw and circular saw manufacturing processes were selected due to the large number of back orders due to increased customer demand and shorter lead time. Metal cutting sawing is a micro-orthogonal process [10] that uses multiple teeth to machine/cut the workpieces; thus, the geometrical features on the saw body require a precise machining process [11], [12]. The hole saw main body is manufactured by welding the tool steel to the tool holder body, machining the tooth form along the tool steel section, and plastically bending the teeth to form the final tooth form[13]. The manufacturing of saw blades includes multiple manufacturing processes with variable throughput rates and complex inspection processes[14], [15]. Thus, the Monte Carlo simulations are required to estimate the lead time and schedule the process flow.

For this study, a detailed review of the inventory quantities that were held of the final product in the shipping department are collected, and the data for the last three months are compared to the Little's Law calculations for accuracy. With customer satisfaction being directly linked to ship time and part-to-part quality being critical, a fine balance of inventory levels and in-process lead times was critical. On the contrary, traditional ideology was needed; the theory states that smaller batch sizes, with reduced setup and non-value added process (NVAP), were used to reduce inventory levels to offset the lead times needed to maintain better process flow. This worked in tandem with a lack of process flexibility to move from part to part at a more fluid rate, resulting in a high level of expedited or "Rush" orders to meet the needs of our customers. Rush orders add unneeded stress to the operators and the manufacturing process. As we continued to develop a better understanding of the actual batch sizes needed, the effect that larger batches had on the material flow, and the step-by-step rate of each process, these inputs were used to formulate optimized material flow that resulted in an original lead time of 25 days, down to 11 days and an increase in shipping accuracy. Due to the smaller batch sizes, it was easier to spot a process deficiency, and as a result, fewer defective parts were made between inspections. The efficiency of these models depends on the amount of historical data [4], and the model's efficiency consistently improves with the more historical data used.

As mentioned, this model was initially applied to the hole-saw manufacturing process to reduce the backorders. As seen in Figure 1, the number of back orders was high during the second and third quarters of 2021. The model was implemented in the third quarter of 2021, the process flow improved, and the back orders reduced considerably, as shown in Figure 1. As we continue to collect historical data from operations, a more granular outline of the process is created, as mentioned by Franke et al [4]. From setup times, takt time per part, and maintenance requirements from planned and unplanned downtime. We can continue to build these variables into the Monte Carlo simulation, which in turn creates much more accurate lead times for future forecasting needs.

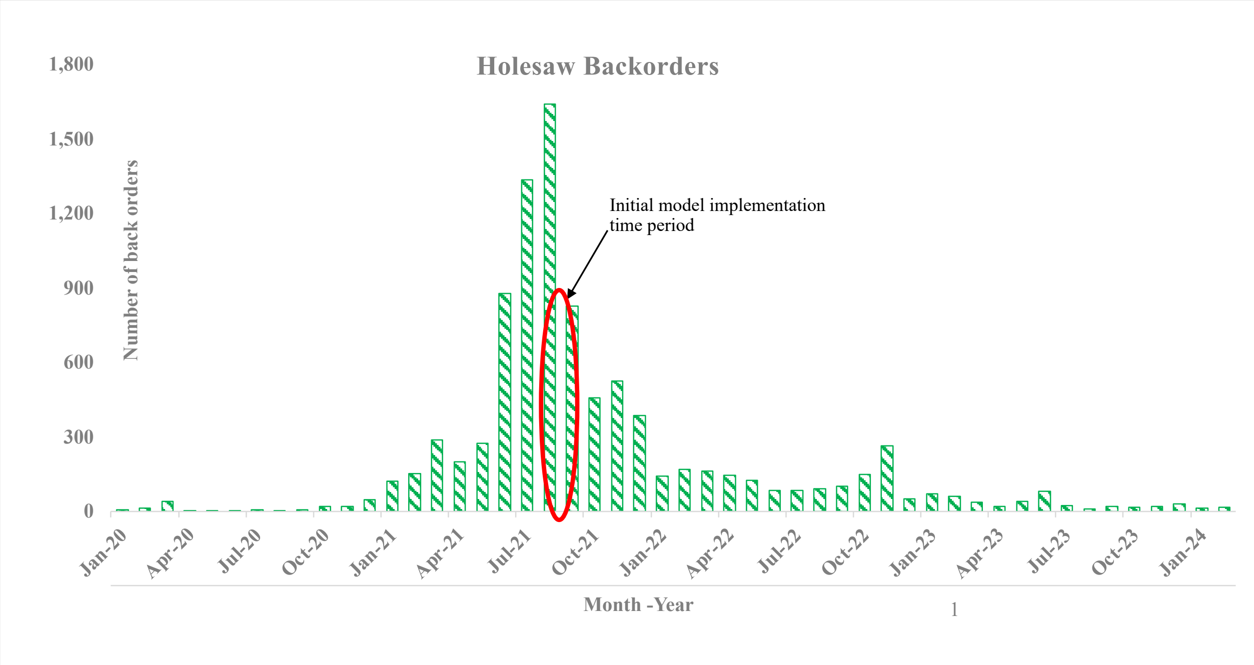

Figure 1: The hole saw backorder reduction due to the implementation of Little's law and Monte Carlo simulation model.

After the initial success of the hole saw backorder reduction, a similar model was implemented on the circular saw manufacturing process in the third quarter of 2023, and by the mid-fourth quarter of 2023, there was a significant reduction in the back orders, as seen in Figure 2. One of the other major reasons for the sustained reduction in the backorders is that the customers were provided with increased probable lead times, thus reducing the uncertainties in the customer order expectations. Our results showing both reduced lead times and decreased backorders support our hypothesis of the application of queuing principles to understand and reduce production lead times. Refining this data through the Monte Carlo simulations provides achievable lead times. One drawback of this model is that a rapid increase in lead time could trigger a larger batch size, thus causing even longer lead times if process improvement is not utilized. A secondary effect of this scheduling model was increased productivity and machine uptime [3]. Two areas showed improvement; one area increased its pieces per labor hour by 10%, while another achieved an 18% improvement. Also, employee morale was affected by the results of this scheduling model. Frustrations with the lack of fulfillment of orders and productivity were reduced.

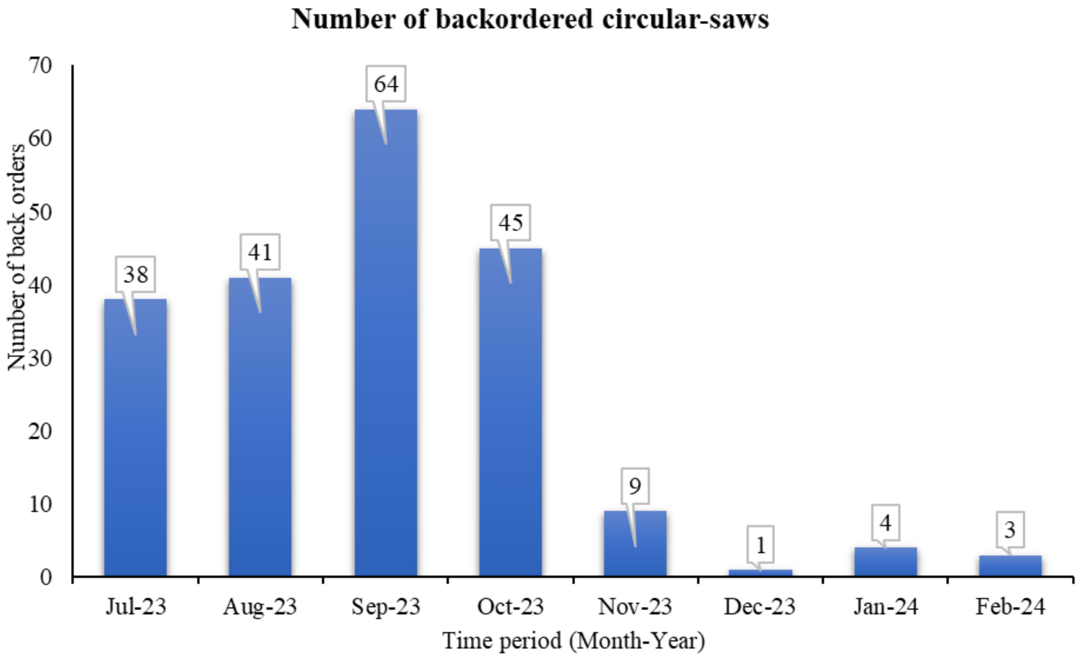

Figure 2: The circular saw backorder reduction is due to the implementation of Little's law and the Monte Carlo simulation model.

4. Conclusion

In this paper, to improve production planning, scheduling, and estimating the lead time, Little's law was used to estimate the initial lead time, and Monte Carlo simulations based on the historical data of the machine-operator-part production rate along with the queuing principles and theory of constraints were used to improve the accuracy of the lead time. The improvements in lead time and real-time backorders were measured to gauge the success of this model. The model was implemented at a cutting tool company to reduce the backorders due to the surge in demand and the supply chain issues. Overall, the results showed that the model has assisted in reducing the lead times and backorders, proving the present study's hypothesis. Using Little's law and Monte Carlo simulation using real-time data has enabled an accurate estimate of the lead time and improved customer satisfaction.

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Biography

Benjamin Grimm: Continuous improvement facilitator at The M. K. Morse Company for over four years. Over the last decade, he has led the production team in the hole-saw manufacturing division, the continuous improvement team.

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