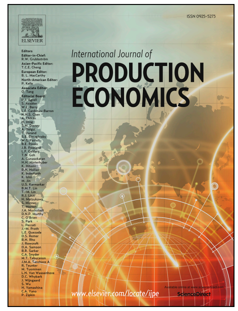

The moderating role of master production scheduling method on throughput in job shop systems

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Abstract

Accurately predicting throughput is a challenging task for managers of manufacturing companies and analytical models for this purpose have been limited to small and simple production systems. Motivated by a complex and real-world case from the automotive industry, this paper first examines how realistically the throughput of complex job shop systems can be predicted based on problem characteristics and different master production scheduling (MPS) approaches. Next, it investigates how different MPS approaches moderate the relationship between problem characteristics and throughput. To achieve these aims, we develop a mixed-effects model based on operational characteristics and the MPS development method to predict the system's throughput. The analyses are based on data from a real-world case in the automotive industry and two complex job shop systems in the literature. The experimental results indicate that the throughput of job shop systems can be predicted with a high level of accuracy ($R^2 = 0.756$) based on the problem's characteristics and that the predictive model cross-validates well on a holdout sample. Moreover, we observed that the MPS method can moderate the impact of problem characteristics reflecting complexity, capacity shortages, and setup requirements on throughput, with moderation especially pronounced in the presence of capacity shortages.

Keywords: Production planning and scheduling; Throughput prediction; Mixed-effects models; Complexity; Capacity shortage

1. Introduction

Predicting the throughput of manufacturing systems has been a challenge for researchers and practitioners over the past few decades. This problem has been exacerbated by several factors, including uncertainty about processing times, complex operation flows, machine breakdowns, and capacity constraints among production resources. Increasing the accuracy of estimates regarding the throughput of production lines can reduce operational costs and penalties that result from delays or lost sales. Accurately predicting throughput can also contribute to customer satisfaction by improving timely deliveries on realistic due dates during sales negotiations. Accurate estimation of throughput during the planning horizon can serve as a proxy for estimating realistic due dates for customer orders. In addition to individual firms, throughput prediction has wider implications at the supply network level. Any change in expected throughput by one member can trigger a domino effect across the whole network.

Previous research in this field focused on the development of analytical models and approximations for throughput estimates of simple production systems with a limited number of work stations and serial process flows under restrictive assumptions about the distribution of processing times. The majority of these studies are validated using simple examples that may not be fair representatives of real-world operations in a job shop system (e.g., Baker et al., 1993; Baker and Powell, 1995; Duenyas and Hopp, 1993; Hopp and Simon, 1989; Liu and Yuan, 2001; Rao and Suri, 1994, 2000; Linhares, 2009). However, scheduling in a job shop system is generally complex (Kern and Wei, 1996; Yang and Jacobs, 1999; Golmohammadi, 2015), especially in a dynamic system with the possibility of shifting bottlenecks (Lawrence and Buss, 1994). To cope with the growing complexity of throughput prediction in real-life applications, and in response to calls for further research to deal with the complexities and uncertainties of actual environments (e.g., Kouvelis et al., 2005), a strand of research has recently emerged that uses data-driven decision-making methods (e.g., Azizi et al., 2015; Huang et al., 2016; Li et al., 2011). Our approach in the current research has been inspired by this trend. We use a data-driven method in addressing our first research question (which will be presented later in this section). In addition to excessive simplicity, another limitation of previous research is the prediction horizon. The majority of the previous prediction models in the literature focus on predicting throughput during the implementation stage (i.e., physical operation) on the shop floor. These investigations ignored the influence of the master production scheduling (MPS) approach and detailed scheduling decisions on throughput. Master production schedule specifies how many of each product should be produced and when. It must be in accordance with the aggregate production plan of the factory (Heizer and Render, 2008). After the production plan has been implemented, the proposed master production schedule or detailed schedule may be very different from the actual throughput. Figure 1 illustrates the scope of the prediction in this paper, which covers three main stages: master production scheduling, detailed scheduling, and implementation on the shop floor. In this schematic flow diagram, rectangles represent 'processes' and arrows represent 'input/output' to/from these processes. Previous research mainly focused on the implementation stage (i.e., stage 3) to predict the output of the shop floor based on detailed schedules. The present research extends the scope of prediction to an earlier stage when demand is known. We should clarify that the aim of this research is not to develop a throughput prediction model, but

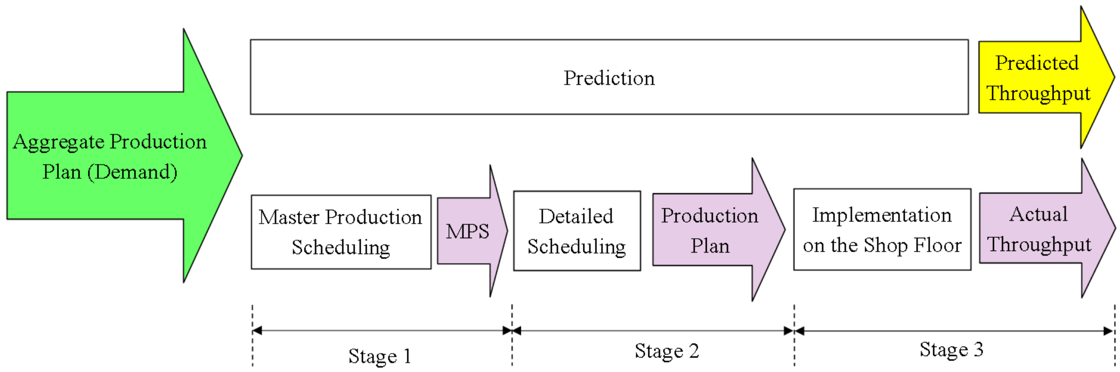

Figure 1: The Scope of Throughput Prediction

to investigate the predictability of throughput in complex job shop systems at an aggregate level and before the MPS development stage to generate managerial insights for production planners and marketing managers. More specifically, we study the factors in job shop systems that influence the actual throughput and the factors that moderate the throughput. We develop a mixed-effects model for our analysis. In other words, the intention here is to develop an analytical tool to explore the dependencies among the variables that can affect throughput and to investigate the moderating role of MPS methods in the relationship between problem characteristics (e.g., operations with setup or without set up) and throughput. In summary, motivated by a real case in the automotive industry, this paper aims to address this gap and to provide managerial insights by addressing two fundamental research questions:

RQ1. How accurate is the prediction of throughput of complex job shop systems based on problem characteristics and before the development of an MPS?

RQ2. Can the MPS method moderate the impact of the influential factors on throughput, and if so, how?

To address these questions, we use three complex job shop systems, including a real case from the automotive industry and two of the most complex job shop cases in the literature. A set of experiments is designed in a diverse set of problem instances (e.g., with or without setup operations) based on the operations flows of these cases. In this way, several configurations of operations flows are generated based on these cases to capture the dynamic nature of operations in job shop systems in different situations, for instance, when a bottleneck feeds another bottleneck or when the operations sequence is complicated. The complexity of the operations, capacity shortage, and setup requirements are considered the three main factors for generating data sets. Simulation models are developed to simulate the production environment and to calculate the throughput of a wide range of problem sets. Using the simulation results, we develop a mixed-effects model (Laird and Ware, 1982) for predicting the throughput of job shop systems based on problem characteristics and MPS methods. The mixed-effects model allows us to answer our research questions and address the non-independence of observations within our simulation scenarios. The moderating role of MPS methods is also investigated through this analysis.

2. Related Literature

The research on throughput prediction was initially focused on analytical models or approximations of serial production systems. Hopp and Simon (1989) provide a review of earlier work in this field up to the 1980s. They also derive bounds and an approximation for the throughput of a two-stage production system, including two processing machines in the first stage and an assembly station in the second stage assuming exponential service times and buffer constraints. Baker et al. (1993) develop a Markov model of a similar production system and calculate the throughput of the system over a range of average processing times using a spreadsheet for exponential processing times. For non-exponential processing times, the authors use a simulation-based methodology for calculating the throughput. They make two extensions to their work and analyzed unbuffered systems with up to five and 20 work stations, respectively using a simulation to calculate the throughput. Duenyas and Hopp (1993) and Duenyas (1994) develop approximations for the throughput of a system consisting of several fabrication lines that feed an assembly line assuming exponential processing times and constant work-in-process. Rao and Suri (1994, 2000) develop analytical models for evaluating the performance of a production system that consists of an assembly station with input from multiple fabrication lines. The authors present approximation algorithms to estimate the throughput and mean queue lengths of these systems with exponential processing times. The solution procedure is a recursive algorithm based on an approximation that involves solving multiple interrelated subnetworks using mean value analysis (MVA). Baker and Powell (1995) develop approximate methods for predicting the throughput of unbalanced three-station assembly systems. The authors present a distribution-free approach for the general case and an approximation that produces analytic results for particular distributions. Liu and Yuan (2001) model a simple two-stage assembly system that includes three work centers as a Markov process and obtain the distribution function of the production flow time. Subsequently, they use the distribution function to estimate the system's throughput.

Analytical tools for predicting throughput have been applied only to simple production systems that include serial (flowshop) operations and restrictive assumptions regarding processing times.

Many production systems are organized as job shops, which are characterized by complex production flows and multiple and changing bottlenecks (Lawrence and Buss, 1994; Yang and Jacobs, 1999; Tsubone et al., 2000; Golmohammadi and Mansouri, 2015). This organization has further limited the applicability of analytical models for throughput prediction in job shop systems. To address these shortcomings, researchers have recently shifted to using data-driven decision making, which is shown to be a powerful approach for prediction in complex environments (e.g., Scala et al., 2014; Cao et al., 2015; Kontar et al., 2017; Batur et al., 2018; De Caigny et al., 2018; Jeong et al., 2018; Li et al., 2018). In this line, Li et al. (2011) develop an autoregressive moving average (ARMA) model to predict the bottleneck of a manufacturing system that defines its throughput. Using historical data, Azizi et al. (2015) construct a Bayesian interface to predict the throughput of a tile production line. The production line studied in their research is a flowshop system with fixed operations flows for all products. Golmohammadi (2013) develops a neural network model, which is focused on detailed scheduling for analysis of job shop scheduling. The proposed model's output helps managers estimate the throughput based on historical data with a trained neural network model instead of a simulation model, which is a costly and complex approach for analysis of scheduling. The main shortcoming of the research is that the training data set may not comprise new problem characteristics, therefore, the prediction results may not be accurate. Huang et al. (2016) develop a simulation assisted neural network to predict the throughput of a production system for thin film transistor liquid crystal display color filter fabs. The forecasting system enables planners to conduct what-if analysis for production control policies without disrupting manufacturing operations. The authors show that the hybrid forecasting system can estimate the throughput of production more quickly. Hadidi and Moawad (2017) employ integer linear programming to formulate the product-mix problem for multiple production lines in sequenced stages in steel industry. Their goals are to provide the maximum throughput for all production stages and avoid production interruptions.

Predicting throughput in job shop systems is more challenging due to the complex operations flows. To the best of our knowledge, prediction of throughput for complex job shop systems and real-world operations have been overlooked in the literature. This paper seeks to close this gap by providing managerial insights into the factors that can influence the throughput of job shop systems and the moderating role of the MPS method in realizing the throughput. For the research community, this paper contributes to the literature on throughput prediction by providing a better understanding of the factors that affect throughput of job shop systems. In this way, this paper paves the way for the advancement of analytical and approximation models for predicting throughput in complex production environments.

3. Methodology

We use a combination of mixed-effects modeling, simulation, and experiment design to answer our research questions. We develop a mixed-effects model based on demand and problem characteristics to predict the throughput of job shop systems before the MPS development stage. Mixed-effects modeling provides a flexible and robust platform for the development of prediction models for complex systems, including multi-stage production systems. An alternative approach to mixed-effects modeling is simulation. However, this approach becomes impractical and a computational chore when the number of alternatives to examine is large (Baker and Powell, 1995). Moreover, simulation modeling needs expert assistance to change the scheduling model (Golmohammadi and Shimshak, 2011; Pegden et al., 1995; Schelasin and Mauer, 1995). Another reason for the use of mixed-effects modeling to generate predictions of throughput vis-à-vis simulation is that they isolate the most important predictors of throughput, thus facilitating managerial decision making by identifying a parsimonious number of system characteristics that are the most influential in throughput. Simulation modeling has been widely used for 'evaluation' purposes, for instance, to evaluate the performance of different production plans and priority rules (e.g., Ardalan and Diaz, 2012; Golmohammadi, 2013). Another benefit of using mixed-effects modeling in this context is that this technique allows us to account for the clustered nature of our data (i.e., the MPS solutions nested within a given experimental scenario). To develop the prediction model, we use simulation modeling and a range of problem instances that cover the key features of the real-world situations in job shop systems. The main features of the research steps are summarized as follows:

- Our prediction model covers three stages: master production scheduling, detailed scheduling, and manufacturing operations (or implementation) on the shop floor (see Figure 1). We use integer linear programming (ILP) and three methods from the literature to develop an MPS in the first stage.
- We then use three job shop production systems to develop the prediction model, including a complex case from the automotive industry and two of the most complex job shop systems from the literature. Several configurations of operations flows are generated based on these cases.
- Based on common recommendations in the literature (Atwater and Chakravorty, 2002; Baker and Trietsch, 2013; Fredendall and Lea, 1997; Goldratt et al., 1986; Golmohammadi and Mansouri, 2015; Kouvelis and Tian, 2014; Pinedo, 2012; Shafer and Charnes, 1993; Sobreiro and Nagano, 2012; de Souza et al., 2013; Sobreiro et al., 2014), we primarily consider six

predictors in three categories: the complexity of the operations, capacity shortage, and setup requirements for the prediction of throughput. These predictors will be defined in details later in Section 3.2.

- Considering two levels for complexity and capacity shortage (high and low) and setup requirements (with and without), we generate 256 data sets based on the three cases for the experiment.
- For detailed scheduling (stage 2), we use the drum-buffer-rope technique (Schragenheim and Ronen, 1990). Flexible rules are defined to prioritize operations on machines in order to maximize throughput. Simulation models in ARENA 13 are developed to simulate the generated operation configurations based on the three cases and to calculate the throughput of the production system (stage 3).
- For the implementation of each MPS, Opt Quest in Arena Software is used to determine the input variables for detailed scheduling, such as batch size or time to release materials.
- The observed throughputs of the four MPS methods for each problem instance are normalized in the interval [0,100] and considered as the dependent variable.
- We use 256 simulation observations for the development and testing of the mixed-effects model. We use a 75% random sample (N = 192 cases) for calibration and the remaining 25% (N = 64 cases) for validation in the current analysis.

In this section, we first explain the methods, which we choose for the master production scheduling, as one of the factors that affects the system's throughput. Subsequently, we provide details of problem generation for the simulation modeling and detailed scheduling. Finally, we discuss the development of the mixed-effects model. To enhance readability, a list of the acronyms used throughout the paper is provided in Table A1 in Appendix A.

3.1. Methods for Master Production Scheduling

We select four MPS methods including an ILP model and three algorithms from the literature: algorithms by Fredendall and Lea (1997) (referred to as FL97), Sobreiro and Nagano (2012) (denoted by SN12), and Golmohammadi and Mansouri (2015) (called GM15). These methods provide reasonable coverage of common MPS development methods as fair representatives of existing methods that consider capacity constraints at an aggregate level. The ILP model is a standard approach and is used by many researchers as a benchmark method in previous research (e.g. Luebbe and Finch, 1992; Plenert, 1993; Aryanezhad and Komijan, 2004). The FL97 algorithm is one of the first heuristic methods in the literature whose focus is on the effective utilization of system constraints. This method is a well-known benchmark in the literature and used by many scholars (e.g. Aryanezhad and Komijan, 2004; Sobreiro and Nagano, 2012; Golmohammadi and Mansouri, 2015). There have been several extensions to FL97 in the literature, and we chose the SN12 algorithm as one of the most recent developments that covers all prior developments in this line. Finally, the GM15 method is one of the most recent algorithms and the only, to the best of our knowledge, method that considers the complexity of operations as an explicit factor in the development of an MPS. A brief outline of these methods is presented in the following subsections.

3.1.1. The ILP Model.

For a problem with n products and m machines, in which a_{ij} represents the processing time of a unit of product i, on machine j, CM_i denotes the contribution margin of product i and CP_j denotes the available capacity of machine j; the following ILP model optimizes the production quantities (Q_i's) subject to demand D_i for product i; $i = 1, \ldots, n$:

$$Maximize \sum_{i=1}^{n} Q_i CM_i \ , \ s.t. : \tag{1}$$

$$\sum_{i=1}^{n} Q_i a_{ij} \leq CP_j \ ; \ j = 1, \ldots, m \tag{2}$$

$$Q_i \leq D_i \ ; \ i = 1, \ldots, n \tag{3}$$

$$Q_i \geq 0 \ ; \ Q_i \in \mathbb{Z} \ ; \ i = 1, \ldots, n \tag{4}$$

Under capacity constraint, this formulation represents a special case of the Knapsack problem, which is known to be NP-hard (Garey and Johnson, 1979).

3.1.2. The FL97 Algorithm

Fredendall and Lea (1997) develop a heuristic method (called FL97 hereafter) to overcome the shortcoming of earlier methods in the presence of multiple constraints in the system. Using numerical examples, the authors first show that traditional methods for product mix decisions (e.g., Goldratt, 1990; Plenert, 1993) face difficulty finding an optimal solution when there is more than one bottleneck (constraint) in the production system. The algorithm is carried out in two main steps. The first step identifies the system's constraints based on the difference between the resources' capacity and the demand on them. The second step determines how to use the system's constraints by considering all candidate bottlenecks. Fredendall and Lea (1997) compare the performance of the FL97 algorithm with Goldratt (1990)'s method and ILP. The authors show that the FL97 algorithm outperforms Goldratt (1990)'s method in terms of throughput. In comparison with ILP, they show that the FL97 method is able to find the same results as ILP but with less computational effort.

3.1.3. The SN12 Algorithm

Sobreiro and Nagano (2012) seek to improve the performance of prior methods for product mix decisions, including the FL97 algorithm, in large instances. The authors propose a constructive heuristic (called SN12 hereafter) based on some components of the FL97 algorithm and a greedy algorithm for the Knapsack problem, which is proposed by Kellerer et al. (2004). The SN12 algorithm first identifies an initial product mix using greedy algorithms for the Knapsack problem (Kellerer et al., 2004). Subsequently, the algorithm improves the initial solution using a neighbourhood search method. Sobreiro and Nagano (2012) compared the performance of their algorithm with two heuristic methods, including the FL97 algorithm and one of its variations developed by Aryanezhad and Komijan (2004), and ILP on small and large data sets. The results indicate that the SN12 algorithm performs better than the two benchmark heuristic methods in terms of throughput and that the performance gap widens as the number of constraints increases. The authors also show that the SN12 algorithm finds the best solution quicker than the benchmark methods.

3.1.4. The GM15 Algorithm

To overcome the limitations of previous methods in the presence of complex operations and capacity shortages, Golmohammadi and Mansouri (2015) develop a heuristic method (called GM15 hereafter). They argue that the calculated throughputs by earlier methods in the literature are not realized during the implementation of the MPS on the shop floor when the production flows are complex and the capacity shortages of the bottlenecks are significant. To address these shortcomings, the GM15 algorithm first identifies bottlenecks using a novel procedure that takes into account the complexity of the operations and the level of capacity shortage in the identification of the system's bottleneck. Next, an initial MPS is developed based on the identified bottleneck. Finally, the initial MPS is improved through a local search. Golmohammadi and Mansouri (2015) design an experiment that included a range of problem instances and compared the performance of the GM15 algorithm with FL97, SN12, and ILP based on static (before the implementation of the MPS on the shop floor) and dynamic (after the implementation of the MPS) throughput using simulation. The results indicate that the GM15 algorithm significantly outperforms the benchmark methods in problems with setup times in terms of dynamic throughput.

For further clarification of the concepts of static and dynamic throughputs, we explain it with an example here. Consider an instance where ILP is employed to determine the optimal production quantities to maximize the throughput (i.e. static throughput). After the implementation of the production plan, the actual throughput (i.e. dynamic throughput) of the operations is most likely different from the results of the ILP method. Such deviation could be due to a number of factors that affect the actual operations such as work-in process, changeover operations and sequence of operations. These factors are not considered during the development of the production plan. Deviations between dynamic and static throughput are expected to be more when operations are complex. These situations happen, for instance, when different parts of one product need to use a constraint machine, or when there are many changeover operations for different products.

3.2. Problem Characteristics

Based on a review of the literature on master production scheduling for job shop systems, we consider six characteristics that are claimed to influence throughput in three categories: the complexity of the operations, capacity shortage, and setup requirements. Below, we introduce the variables in each category.

- **Complexity of operations**. Goldratt et al. (1986) argue that two factors affect the complexity of operations. These factors include the complexity of flow and the number of products that need the same machine. Golmohammadi and Mansouri (2015) demonstrate that the complexity of the operations can significantly affect the realized throughput and define a complexity index as a function of the number of products that need a machine and the total number of times a machine is required to process all parts. This index reflects not only the dependence between products and machines but also the total number of visits to the machine capturing the loops and cyclic operations. The level of complexity (denoted by ComplexityLevel) in a problem is specified according to the number of complex machines. We use Golmohammadi and Mansouri (2015)'s classification for categorizing problems that have high and low ComplexityLevel. To distinguish between problems at the same level of complexity, we consider the Ratio of Complex Machines (RCM), the number of complex machines to the total number of machines, as another indicator of complexity. Moreover, we consider the dependence between machines and products as another indicator of complexity (Shafer and Charnes, 1993). For this, we use the Density of Part-Machine Incidence Matrix (DPMIM) metric, which is the ratio of the non-zero elements of the part-machine incidence matrix (i.e., elements with $a_{ij} > 0$) to total number of elements of the matrix (i.e., $n \times m$). In sum, the three characteristics that reflect the complexity of the operations include ComplexityLevel (categorical variable at two levels, low and high), RCM (scale variable between 0 and 1), and the DPMIM (scale variable between 0 and 1).

- **Capacity shortage**. Many scholars argue that capacity shortage is one of the main factors that influence the realization of anticipated throughput (e.g., Atwater and Chakravorty, 2002; Fredendall and Lea, 1997; Kouvelis and Tian, 2014; Sobreiro and Nagano, 2012). Accordingly, we consider CapacityShortage at two levels, low and high to categorize problems in this respect. Capacity Shortage is considered high if more than half of the machines are under capacity to meet the demand and is considered low otherwise. To account for the variations among the problems with the same level of CapacityShortage, we define the Ratio of Under-Capacity Machines (RUCM) as another indicator of shortage in capacity. RUCM simply measures the ratio of under-capacity machines (with reference to demand) to the total number of machines. In short, the two problem characteristics regarding the capacity factor are CapacityShortage (categorical variable at two levels low and high) and RUCM (scale variable between 0 and 1).
- **Setup requirements**. We consider setup requirements (denoted by Setup) in a problem as another characteristic that can affect the realized throughput. Problems with Setup are subject to more uncertainty in utilizing the available time on machines (Baker and Trietsch, 2013; Pinedo, 2012). Setup refers to the preparations that can be made only when the machine is not in use. Off-line and negligible setups (such as tool changes in a Computer Numerical Controlled (CNC) machine) are not considered here as Setup. Finally, Setup is represented by a binary variable in the mixed-effects model.

3.3. Problem Generation

Three job shop production systems are used to develop the prediction model: a complex production system from the automotive industry and two of the most complex job shop systems from Hsu and Chung (1998) and Atwater and Chakravorty (2002). The automotive case problem (denoted by AutoCase hereafter) is adapted from a manufacturer of exhaust parts that uses a job shop system. For this research, we select five products: A, B, C, D, and E. Product B requires two raw materials, B1 and B2. In total, there are 16 different machines in the production system (M1 to M16) with only one of each type available for operations. The operations routes of the products are summarized in Table 1. Additional details of the AutoCase are presented in Appendix B. They include processing and setup times for products A and C (Table B1), products B1 and B2 (Table B2), and products D and E (Table B3). Finally, Table B4 summarizes the aggregate processing times, demands during the planning horizon (one month), contribution (profit) margins of the products and the machines' available capacities.

Table 1: Operations Routes of the Products in the AutoCase Problem

Products	Operations routes
A	M8-M7-M7-M3-M5-M3-M5-M4-M4-M5-M2-M2-M7-M7
B1	M1-M5-M6-M5-M5-M4-M6-M5-M4-M3-M1-M10-M11
B2	M9-M12-M4-M11
C	M9-M12-M4-M6-M6-M12-M16-M6-M12-M13-M13-M14-M15-M16
D	M1-M2-M4-M5-M4-M5-M7-M8-M13
E	M1-M4-M5-M4-M5-M4-M6-M7

We choose the AutoCase problem because it represents a highly complex situation and is similar to most real-world job shop systems. In addition, we select two of the most commonly used benchmark problems from the literature. They include the problem by Hsu and Chung (1998) (denoted by HC98) that contains four products and seven machines and the problem by Atwater and Chakravorty (2002) (coded as AC02) that include 10 products and 13 machines. These cases represent the most complex problems that we are able to find in the literature. Consequently, 32 scenarios are generated based on these three case problems. For this, we consider the complexity of the operations at two levels (low and high) and the capacity shortage at two levels (low and high) as the two main factors for the generation of data sets. Table 2 shows the spread of the problem instances across the two dimensions: the complexity of the operations and capacity shortage. Finally, each problem is considered in two variants: with and without setup resulting in $32 \times 2 = 64$ test problems. Each problem is solved using the four MPS solution methods described in Section 3.1, i.e., ILP, FL97, SN12, and GM15. This resulted in $64 \times 4 = 256$ observations, which are used to develop the prediction model.

Table 2: Distribution of 32 Problem Instances Generated from the Three Base Problems

			Level of operations' complexity	
		Base problem	Low	High
Level of capacity shortage	Low	HC98	2	3
		AC02	3	2
		AutoCase	3	3
	High	HC98	3	2
		AC02	3	3
		AutoCase	2	3

3.4. Simulation Setup and Detailed Scheduling

Three of the MPS solution methods, namely, the FL97, SN12 and GM15 algorithms, are coded in C++. Excel Solver is used to solve the ILP models. The MPS that is found by the four solution methods is then inputted in simulation models of the respective production systems as defined by the test problems. ARENA 13 is used to simulate the production environment and to calculate the throughput of the production system. The simulation models are run for a period of 14,400 minutes for the instances derived from the AutoCase, 2,400 minutes for HC98 and 2,040 minutes for AC02, respectively, based on the original described case information. The ARENAs animation capability and verication techniques ensure that the assumptions and parameters are correctly considered in the simulation models. One of the assumptions is that there are no defective parts or machine failure. Demands are satisfied as much as possible during the operation periods and based on the available capacities of the machines. The simulation models are run for defined operation periods for each problem instance and then stopped. Following Kelton et al. (2009)'s guidelines, we do not consider warm-up periods to reach steady states. The designed models start out empty of parts, and all resources are considered to be ideal. This is a terminating system situation, and therefore, no warm-up is required to ignore the initial conditions.

For detailed scheduling the same scheduling techniques for all MPS methods have been implemented. We use the drum-buffer-rope technique (Schragenheim and Ronen, 1990) in all the models. Flexible rules are defined to prioritize operations on machines in order to maximize throughput. In this way, products with higher marginal contributions are given priority unless there is a product in the final stage of operations. In this situation, the original priority rule is overridden to reduce the WIP and to increase throughput. These rules are assessed through simulation modeling tests and verified accordingly. Opt Quest optimization software is used to determine the detailed schedules by searching for optimal solutions within the ARENA simulation models. For each MPS implementation, input variables for detailed scheduling, such as inter-arrival times between batches, and arrival batch sizes, are determined by Opt Quest to increase throughput. The models are simulated for 1,000 runs with 30 iterations in each run. It should be noted that detailed scheduling method cannot affect NT in our experiments because we utilize drum-buffer-rope technique for all MPS methods. Thus, this factor is constant and cannot consequently affect the results of the scenarios.

4. Prediction Model

In this section, we develop a mixed-effects model to study the throughput of job shop systems based on problem characteristics and the four MPS methods introduced in Section 3.1. The intention here is to develop an analytical tool to explore the dependencies among the variables that can affect throughput and to investigate the moderating role of MPS methods in the relationship between problem characteristics and throughput. Table 3 provides the list of notations used for the development of the mixed-effects model.

Table 3: List of Notations used in the Mixed-Effects Model

Item	Definition
n :	Number of products
m :	Number of machines
i :	Index for products; $i = 1, \ldots, n$
j :	Index for machines; $j = 1, \ldots, m$
k :	Index for MPS methods; $k = 1, \ldots, 4$
ℓ :	Index for problem sets; $\ell = 1, \ldots, 64$
a_{ij} :	Processing time of a unit of product i on machine j
CM_i :	Contribution margin of product i
CP_j :	Available capacity of machine j
Q_i :	Production quantity of product i
D_i :	Demand for product i
$NT_{k\ell}$:	Normalized throughput of problem set ℓ obtained by MPS method k
$AutoCase_\ell$:	Binary variable, which takes '1' if problem set ℓ belongs to the AutoCase and '0' otherwise
$HC98_\ell$:	Binary variable, which takes "1' if problem set ℓ belongs to the HC98 and '0' otherwise
$AC02_\ell$:	Binary variable, which takes "1' if problem set ℓ belongs to the AC02 and '0' otherwise
$ComplexityLevel_\ell$:	Complexity level of problem set ℓ ('low' or 'high')
RCM_ℓ :	Ratio of complex machines in problem set ℓ ($\in [0, 1]$)
$DPMIM_\ell$:	Density of part-machine incidence matrix in problem set ℓ ($\in [0, 1]$)
$CapacityShortage_\ell$:	Capacity shortage level of problem set ℓ ('low' or 'high')
$RUCM_\ell$:	Ratio of under-capacity machines in problem set ℓ ($\in [0, 1]$)
$Setup_\ell$:	Binary variable, which takes '1' if problem set ℓ has setup requirements and '0' otherwise
$FL97_{k\ell}$:	Categorical variable, which takes '-1' if the MPS method used to solve problem set ℓ is ILP,'1' if it is FL97 and '0' otherwise
$SN12_{k\ell}$:	Categorical variable, which takes '-1' if the MPS method used to solve problem set ℓ is ILP, '1' if the MPS method is SN12 and '0' otherwise
$GM15_{k\ell}$:	Categorical variable, which takes '-1' if the MPS method used to solve problem set ℓ is ILP, '1' if the MPS method is GM15 and '0' otherwise

4.1. Dependent Variable

In line with earlier research (e.g., Fredendall and Lea, 1997; Golmohammadi and Mansouri, 2015; Sobreiro and Nagano, 2012), we consider the monetary value of the actual produced items of a job shop system as its throughput (T). Using the notation in Section 3.1.1, the system's throughput can be calculated as follows:

$$T = \sum_{i=1}^{n} Q_i CM_i \ , \tag{5}$$

in which Q_i and CM_i represent the production quantity and the contribution margin of product i, respectively. Recall that we have 64 test problems, 20 for HC98, 22 for AC02, and 22 for AutoCase. Within each test problem, we have the throughput for each of the four MPS methods (ILP, FL97, SN12, and GM15), resulting in a total of N = 256 data points. To make the throughput comparable across the three cases, we normalize throughput within each case by dividing the throughput for a given test problem-MPS method combination by the maximum throughput obtained within a given case. Normalizing the data by the highest throughput in each scenario neutralizes differences that arise due to differences in product value and overall units produced in each scenario. This results in a measure that falls within the range $[0, 1]$, which we then scale by 100 to create our dependent variable that we term Normalized Throughput (NT). As shown in Figure 2, NT is approximately normally distributed, with a one-sample Kolmogorov-Smirnov test for whether NT is normally distributed being non-significant ($D = 0.0526,\ p = 0.084$).

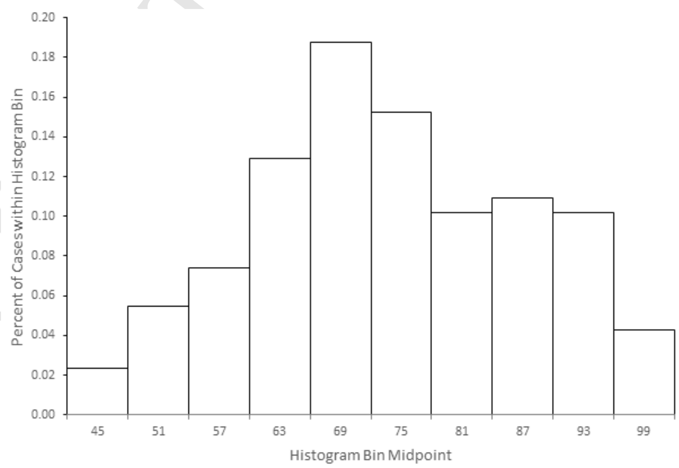

Figure 2: Histogram of Normalized Throughput

4.2. Predictors

Based on the 13 items discussed in Sections 3.1 to 3.3, including four MPS methods, six problem characteristics, and three cases, we consider 11 predictors that may affect NT and thus, we include in our analysis model. Although there are 13 predictors, we only include 11 variables in the model because two sets of predictors are categorical vectors whereby we must remove one of the predictors from each vector to avoid creating a linear combination that would cause an estimation failure in the mixed-effects model. As we examine three cases, we include two dummy variables for AutoCase (AutoCase) and HC98 (HC98)–treating AC02 as the omitted category–to control for stable between-case differences that may affect NT. We include a dummy variable denoted as ComplexityLevel that equals 0 for low and 1 for high complexity test problems (as defined in Section 3.2). We include the RCM (Section 3.2) as the second measure of complexity. We mean-center this predictor before conducting the analysis to improve parameter interpretability. We include a third measure of complexity that is denoted as DPMIM, which is defined in Section 3.2. We mean-center this predictor before we conduct the analysis to improve parameter interpretability.

We include two measures that capture capacity issues. The first, denoted as CapacityShortage, is a binary variable that equals 0 for low and 1 for high capacity shortage scenarios. The second, is RUCM (Section 3.2) that we mean-center before we conduct the analysis to improve parameter interpretability. We also include a measure that indicates whether setup requirements are necessary. This measure, denoted as Setup, is a binary variable that equals 0 for problem sets with no setup requirements and 1 for problem sets with setup requirements. Last, we include predictors that represent the MPS methods described in Section 3.1. We do this using unweighted effect coding (Cohen et al., 2003) where we treat ILP as the omitted category. The three binary predictors, denoted as FL97, SN12, and GM15, thus represent the difference in NT for each MPS method vis-à-vis the unweighted average across all four MPS methods (Hand and Crowder, 1996). As will be elaborated upon, this coding scheme is particularly well-suited to examine the research questions.

4.3. Detailed Research Questions

According to the independent variables (i.e., predictors), we can now provide a more detailed level of the two research questions set out in Section 1 as follows:

RQ1. How realistic is it to predict the throughput of job shop systems based on problem characteristics and the MPS method?

RQ2. Given that the problem characteristics can be categorized in three groups, (1) complexity (ComplexityLevel, RCM, DPMIM), (2) capacity shortage (CapacityShortage, RUCP), and

(3) setup requirements (Setup), how can the MPS method moderate the impact of these categories on throughput? More specifically:

RQ2.1. How can the MPS method moderate the impact of complexity on NT?

RQ2.2. How can the MPS method moderate the impact of capacity shortage on NT?

RQ2.3. How can the MPS method moderate the impact of setup requirements on NT?

4.4. Statistical Methodology

Given that the N = 256 cases are nested within 64 test problems, it is likely that the residuals within a test problem are correlated. As the resulting 4×4 residual covariance matrix for each test problem represents the residual variances and covariances across the four MPS methods, it would be inappropriate to assume that the residual variances are equal and the residual covariances are constant. Thus, we model the residual covariance matrix using an unstructured pattern with the mixed-effects modeling framework (Fitzmaurice et al., 2011; Hand and Crowder, 1996; Hoffman, 2015). Letting k index the MPS methods such that $k = 1, 2, 3, 4$ represent ILP, FL97, SN12, and GM15, respectively, and letting ℓ index problem sets, the regression component of the model can be written as follows:

$$\begin{aligned} NT_{k\ell} =& \beta_0 + \beta_1 AutoCase_\ell + \beta_2 HC98_\ell + \beta_3 ComplexityLevel_\ell + \beta_4 RCM_\ell + \\ & \beta_5 DPMIM_\ell + \beta_6 CapacityShortage_\ell + \beta_7 RUCM_\ell + \beta_8 Setup_\ell + \\ & \beta_9 FL97_{k\ell} + \beta_{10} SN12_{k\ell} + \beta_{11} GM15_{k\ell} + \varepsilon_{k\ell} \end{aligned} \tag{6}$$

The covariance matrix for the residuals within each problem set, denoted as $\boldsymbol{R}$, can be written as shown in Equation (7). In Equation (7), σ_1^2 represents the estimated residual variance of NT for the ILP across the 64 problem sets, σ_2^2 represents the estimated residual variance of NT for the FL97 across the 64 problem sets, etc. Similarly, σ_{21} represents the covariance for the residuals for ILP and FL97 within a problem set across the 64 problem sets, σ_{31} represents the covariance for the residuals for ILP and SN12 within a problem set across the 64 problem sets, etc. We estimate all mixed-effects models using full information maximum likelihood as implemented in the PROC MIXED routine in SAS 9.4.

$$\boldsymbol{R} = \begin{bmatrix} \sigma_1^2 & & & \\ \sigma_{21} & \sigma_2^2 & & \\ \sigma_{31} & \sigma_{32} & \sigma_3^2 & \\ \sigma_{41} & \sigma_{42} & \sigma_{43} & \sigma_4^2 \end{bmatrix} \tag{7}$$

To answer the first research question, we randomly select 75% of our cases to form a calibration sample ($N_c = 192$) and then fit the model captured in Equations (6) and (7) to this sample. We then utilize the parameter estimates from Equation (6) to conduct a cross-validation analysis by using these parameter estimates to generate the predicted NT for the remaining 25% of the cases in the validation sample ($N_v = 64$). We then correlate the predicted and observed NT scores for each case in the validation sample and square this correlation to obtain the R^2 (Browne, 2000).

To answer the second research question, we expand upon our prior model and include interaction terms between each MPS method and the characteristics of each individual problem set. We analyze each set of interactions separately for each characteristic to improve interpretability. Given the use of unweighted effect coding for the MPS methods, the resulting interaction terms can be interpreted as the extent the use of an MPS method results in a characteristic having a more positive (negative) effect on NT vis-à-vis the average effect of the characteristic across the MPS methods (Hand and Crowder, 1996).

5. Results and Discussion

In this section, we provide answers to the detailed research questions set out in Section 4.3. Results from fitting the mixed effects model represented in Equations (6) and (7) to the calibration sample can be found in Table 4.

An examination of model diagnostics suggests the residuals are approximately normal, and no influential observations unduly affect results. Overall, the model performs very well regarding predictive accuracy, with an R^2 of 0.756. Inspection of the results in Table 4 indicates that the three sets of predictors have ceteris paribus effects on NT. First, the two dummy variables for AutoCase and HC98 are statistically significant as a set ($\Delta\chi^2 = 8.6$ with 2 DF [$p < 0.05$]), and indicate that on average NT is higher for the AutoCase and HC98 problem sets vis-à-vis AC02. Second, Setup is significant and negative, indicating that NT is approximately 21.87 lower when setup requirements exist. Third, the three effect coded variables for FL97, SN12, and GM15 are significant as a set ($\Delta\chi^2 = 34.7$ with 3 DF [$p < 0.01$]). Looking at the estimated parameters, the results indicate that the FL97 algorithm has a predicted NT that does not differ from the unweighted mean across the MPS methods. The significant negative estimate for SN12 indicates that this algorithm predicts an NT that is less than the unweighted mean across the MPS methods. The significant positive estimate for GM15 indicates that this algorithm predicts an NT that is higher than the unweighted mean across the MPS methods.

Table 4: Results from Mixed-Effects Model Fit to the Calibration Sample

		Model 1
Fixed Effects		
	Intercept	80.47**
		(28.29)
	AutoCase	9.07**
		(3.13)
	HC98	14.97**
		(2.90)
	ComplexityLevel	-3.60
		(-1.06)
	RCM	9.56
		(0.72)
	DPMIM	-24.49
		(-1.34)
	CapacityShortage	-2.78
		(-0.86)
	RUCM	0.34
		(0.04)
	Setup	-21.87**
		(-15.53)
	FL97	0.05
		(0.15)
	SN12	-2.83**
		(-5.47)
	GM15	2.24**
		(7.28)
Variance Components		
	Var. ILP	41.41**
	Var. FL97	35.15**
	Var. SN12	44.40**
	Var. GM15	51.44**
	Cov. ILP, FL97	32.95**
	Cov. ILP, SN12	25.14**
	Cov. FL97, SN12	27.15**
	Cov. ILP, GM15	40.94**
	Cov. FL97, GM15	36.76**
	Cov. SN12, GM15	36.56**
Measures of Fit		
	-2 Log Likelihood	1102.1
	R^2 Fixed Effects	0.756

$^{\dagger} = p < 0.01, ^{*} = p < 0.05, ^{**} = p < 0.01$ (two-tailed)
R^2 calculated by squaring the correlation between the predicted NT for the fixed effects and the observed NT per Hoffman (2015).

To conduct the cross-validation analysis, we utilize the parameter estimates for the mixed-effects coefficients in Table 4 to generate the prediction of NT for the 64 observations in the validation sample. We then calculate the correlation between the predicted NT and the observed NT and square this correlation (i.e., an R^2 for the validation sample) to evaluate the model's predictive accuracy (Browne, 1975). Ideally, one hopes to see the predictive accuracy in the validation sample not deteriorate drastically from the predictive accuracy in the calibration sample because this would indicate the model is capturing idiosyncratic sample characteristics, as opposed to capturing facets of the underlying process that gives rise to the data (Browne, 2000). The R^2 for the validation sample is found to be 0.733, suggesting the model captures the fundamental factors that affect NT. The cross-validation analysis is also completed by refitting the model to the calibration sample using only the significant predictors from the full model and then using the estimated mixed-effects coefficients from this reduced model to generate predicted values for the calibration sample. The R^2 in the calibration sample for the reduced model is 0.688. Thus, while the models perform similarly, the full model exhibits higher predictive accuracy and is retained (Browne, 1975).

We now turn our attention to the second research question concerning how MPS methods moderate the effects of problem characteristics on NT. We report these results in Tables 5 to 7 where we refit Equation (6) and (7) to the full sample and then include the appropriate interaction terms between the MPS methods. We evaluate whether the addition of the three interaction terms results in a significant improvement in model fit using $\Delta\chi^2$ tests (Hoffman, 2015). Beginning with Model 1 in Table 5, we see nearly identical conclusions as those that are reached when the calibration sample is used, with the only change the parameter for DPMIM being marginally significant ($p < 0.10$) and negative. Given the strong performance in the cross-validation analysis, the similarity of results is to be expected.

Examining the sets of interaction terms, we see that four of the six problem set characteristics have significant sets of interactions. Turning first to Model 3 in Table 5, we see that RCM displays a statistically significant positive interaction with SN12. Given the use of unweighted effect coding, we can interpret this finding to mean that relative to the unweighted mean across the MPS methods (Hand and Crowder, 1996), use of SN12 results in RCM having a less negative (more positive) effect of NT. To better understand this interaction, in Figure 3 we plot the interaction according to Aiken et al. (1991). As can be seen in Figure 3, the likely reason the RCM has a more positive coefficient for SN12 vis-à-vis the unweighted mean across the MPS methods is that, on average, SN12 results in a lower NT across the range of RCM. Moreover, Figure 3 indicates that across the range of RCM, GM15 displays the highest NT. Thus, while SN12's performance improves more rapidly relative to

Table 5: Results from Mixed-Effects Model Fit to the Full Model and Interactions of the MPS Methods with ComplexityLevel and the RCM

	Model 1	Model 2	Model 3
Fixed Effects			
Intercept	79.11** (27.75)	78.80** (27.53)	79.11** (27.76)
AutoCase	10.29** (3.51)	10.29** (3.51)	10.29** (3.51)
HC98	16.37** (3.18)	16.37** (3.18)	16.37** (3.18)
ComplexityLevel	-2.68 (-0.79)	-2.05 (-0.60)	-2.68 (-0.79)
RCM	13.06 (0.99)	13.06 (0.99)	14.59 (1.10)
DPMIM	-34.83† (-1.93)	-34.83† (-1.93)	-34.83† (-1.93)
CapacityShortage	-2.65 (-0.82)	-2.65 (-0.82)	-2.65 (-0.82)
RUCM	-0.79 (-0.09)	-0.79 (-0.09)	-0.79 (-0.09)
Setup	-22.17** (-15.69)	-22.17** (-15.69)	-22.17** (-15.69)
FL97	-0.05 (-0.20)	0.21 (0.55)	-0.05 (-0.20)
SN12	-2.88** (-7.31)	-3.52** (-6.44)	-2.88** (-7.77)
GM15	2.38** (8.22)	2.18** (5.34)	2.38** (8.23)
ComplexityLevel × FL97		(0.53) (-0.98)	
ComplexityLevel × SN12		1.27 (1.64)	
ComplexityLevel × GM15		0.40 (0.69)	
RCM × FL97			(1.07) (-0.97)
RCM × SN12			4.36** (2.87)
RCM × GM15			0.58 (0.49)
Variance Components			
Var. ILP	37.88**	37.83**	37.56**
Var. FL97	39.65**	39.65**	39.63**
Var. SN12	44.09**	43.19**	42.02**
Var. GM15	50.56**	50.29**	50.29**
Cov. ILP, FL97	31.26**	31.28**	31.33**
Cov. ILP, SN12	27.65**	27.89**	28.47**
Cov. FL97, SN12	32.41**	32.35**	32.25**
Cov. ILP, GM15	36.72**	36.85**	37.02**
Cov. FL97, GM15	38.90**	38.87**	38.84**
Cov. SN12, GM15	36.63**	36.14**	35.89**
Measures of Fit			
-2 Log Likelihood	1448.6	1443.5	1436.5
$\Delta\chi^2$		5.1	12.1**
R^2 Fixed Effects	0.755	0.756	0.758

$^{\dagger} = p < 0.01, ^{*} = p < 0.05, ^{**} = p < 0.01$ (two-tailed)
R^2 calculated by squaring the correlation between the predicted NT for the fixed effects and the observed NT per Hoffman (2015).

Table 6: Results from Mixed-Effects Model Fit to the Full Model and Interactions of the MPS Methods with the DPMIM and CapacityShortage

	Model 4	Model 5	Model 6
Fixed Effects			
Intercept	79.11** (27.75)	79.11** (27.76)	78.52** (27.45)
AutoCase	10.29** (3.51)	10.29** (3.51)	10.29** (3.51)
HC98	16.37** (3.18)	16.37** (3.18)	16.37** (3.18)
Complexity Level	-2.68 (-0.79)	-2.68 (-0.79)	-2.68 (-0.79)
RCM	13.06 (0.99)	13.06 (0.99)	13.06 (0.99)
DPMIM	-34.83† (-1.93)	-32.05† (-1.77)	-34.83† (-1.93)
CapacityShortage	-2.65 (-0.82)	-2.65 (-0.82)	-1.47 (-0.45)
RUCM	-0.79 (-0.09)	-0.79 (-0.09)	-0.79 (-0.09)
Setup	-22.17** (-15.69)	-22.17** (-15.69)	-22.17** (-15.69)
FL97	-0.05 (-0.20)	-0.05 (-0.20)	-0.42 (-1.13)
SN12	-2.88** (-7.31)	-2.88** (-7.35)	-1.73** (-3.34)
GM15	2.38** (8.22)	2.38** (8.33)	1.60** (4.15)
DPMIM × FL97		0.37 (0.24)	
DPMIM × SN12		1.74 (0.80)	
DPMIM × GM15		2.14 (1.35)	
CapacityShortage × FL97			0.75 (1.39)
CapacityShortage × SN12			-2.29** (-3.12)
CapacityShortage × GM15			1.56** (2.85)
Variance Components			
Var. ILP	37.88**	37.82**	37.55**
Var. FL97	39.65**	39.33**	38.72**
Var. SN12	44.09**	43.43**	43.79**
Var. GM15	50.56**	49.78**	48.69**
Cov. ILP, FL97	31.26**	31.41**	30.70**
Cov. ILP, SN12	27.65**	27.87**	27.98**
Cov. FL97, SN12	32.41**	31.95**	32.94**
Cov. ILP, GM15	36.72**	36.96**	35.93**
Cov. FL97, GM15	38.90**	38.40**	37.58**
Cov. SN12, GM15	36.63**	35.91**	37.39**
Measures of Fit			
-2 Log Likelihood	1448.6	1442.3	1434.4
$\Delta\chi^2$		6.3	14.2**
R^2 Fixed Effects	0.755	0.757	0.759

$^{\dagger} = p < 0.01, ^{*} = p < 0.05, ^{**} = p < 0.01$ (two-tailed)
R^2 calculated by squaring the correlation between the predicted NT for the fixed effects and the observed NT per Hoffman (2015).

Table 7: Results from Mixed-Effects Model Fit to the Full Model and Interactions of the MPS Methods with the RUCM and Setup

		Model 7	Model 8	Model 9
Fixed Effects				
	Intercept	79.11** (27.75)	79.11** (27.76)	78.21** (27.37)
	AutoCase	10.29** (3.51)	10.29** (3.51)	10.29** (3.51)
	HC98	16.37** (3.18)	16.37** (3.18)	16.37** (3.18)
	Complexity Level	-2.68 (-0.79)	-2.68 (-0.79)	-2.68 (-0.79)
	RCM	13.06 (0.99)	13.06 (0.99)	13.06 (0.99)
	DPMIM	-34.83† (-1.93)	-34.83† (-1.93)	-34.83† (-1.93)
	CapacityShortage	-2.65 (-0.82)	-2.65 (-0.82)	-2.65 (-0.82)
	RUCM	-0.79 (-0.09)	1.92 (0.21)	-0.79 (-0.09)
	Setup	-22.17** (-15.69)	-22.17** (-15.69)	-20.37** (-13.69)
	FL97	-0.05 (-0.20)	-0.05 (-0.20)	0.80** (2.25)
	SN12	-2.88** (-7.31)	-2.88** (-7.47)	-2.79** (-5.01)
	GM15	2.38** (8.22)	2.38** (8.50)	1.30** (3.58)
	RUCM × FL97		1.44 (1.00)	
	RUCM × SN12		-3.39 (-1.65)	
	RUCM × GM15		3.15* (2.11)	
	Setup × FL97			-1.70** (-3.40)
	Setup × SN12			-0.18 (-0.23)
	Setup × GM15			2.17** (4.23)
Variance Components				
	Var. ILP	37.88**	37.81**	37.31**
	Var. FL97	39.65**	39.04**	39.65**
	Var. SN12	44.09**	44.08**	43.43**
	Var. GM15	50.56**	49.35**	46.61**
	Cov. ILP, FL97	31.26**	31.04**	31.22**
	Cov. ILP, SN12	27.65**	27.69**	27.03**
	Cov. FL97, SN12	32.41**	32.51**	32.37**
	Cov. ILP, GM15	36.72**	36.41**	35.21**
	Cov. FL97, GM15	38.90**	38.05**	38.80**
	Cov. SN12, GM15	36.63**	36.77**	35.01**
Measures of Fit				
	-2 Log Likelihood	1448.6	1441.8	1425.1
	$\Delta\chi^2$		6.8†	23.5**
	R^2 Fixed Effects	0.755	0.756	0.757

$^{\dagger} = p < 0.01, ^{*} = p < 0.05, ^{**} = p < 0.01$ (two-tailed)
R^2 calculated by squaring the correlation between the predicted NT for the fixed effects and the observed NT per Hoffman (2015).

the unweighted mean across the MPS methods as RCM increases, this more rapid improvement does not allow the technique to outperform GM15. With this being said, it is important to recall that the three measures of complexity have a limited relationship with NT, and thus, the limited evidence of moderation should not be viewed as problematic.

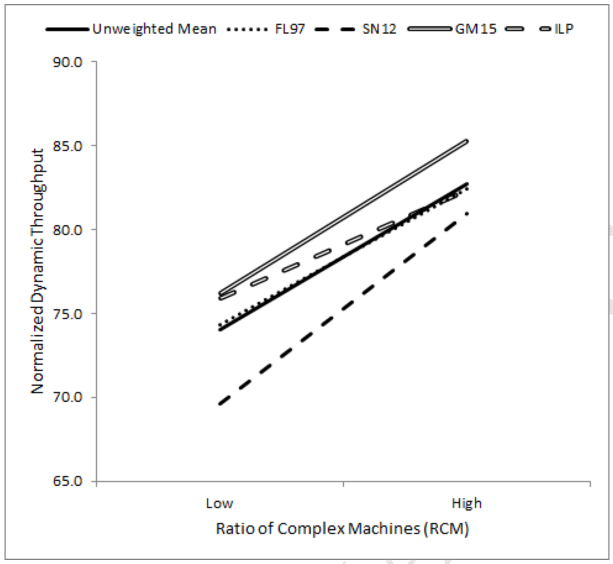

Figure 3: Plot of the Predicted NT for the Interaction between the RCM and the MPS Methods

We now examine the significant set of interactions between CapacityShortage and the MPS methods. The statistically significant negative interaction with SN12 indicates SN12 performs more poorly than the unweighted average across the MPS methods when there is a capacity shortage. In contrast, the significant positive interaction with GM15 indicates it performs better than the unweighted average across the MPS methods when there is a capacity shortage. This is illustrated clearly in Figure 4. Importantly, GM15 again outperforms all the remaining MPS methods and has the ability to mitigate the negative consequences of capacity shortages on NT. Thus, the takeaway from Figure 4 is that in scenarios with capacity shortages GM15 is the preferred algorithm and SN12 should be avoided.

The third significant set of interaction terms involves the RUCM, with the interaction between the RUCM and GM15 statistically significant and positive, indicating that the positive effect of the RUCM on NT is more pronounced when GM15 is utilized vis-à-vis the unweighted mean across the MPS methods. As shown in Figure 5, the striking feature of this finding is that GM15 displays a higher NT across the range of the RUCM. This illustrates that not only is GM15 preferred when there is a capacity shortage, but also the algorithm can further enhance NT when more machines are operating under capacity.

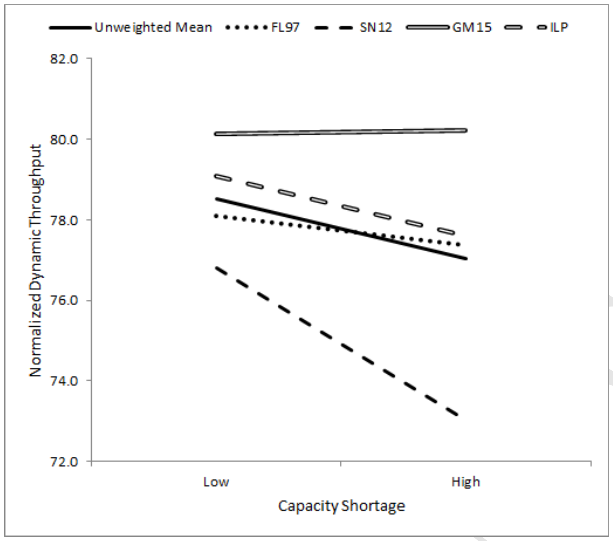

Figure 4: Plot of the Predicted NT for the Interaction between CapacityShortage and the MPS Methods

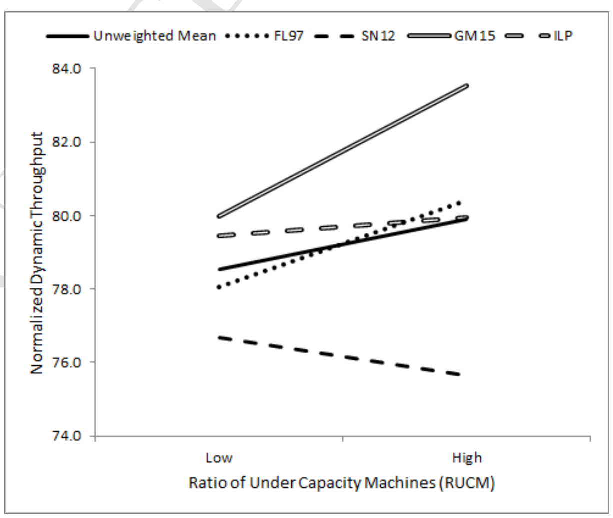

Figure 5: Plot of the Predicted NT for the Interaction between the RUCM and the MPS Methods

The final significant set of interactions terms involves Setup, which has a statistically significant negative interaction with FL97 and a statistically significant positive interaction with GM15. This result indicates that FL97 exacerbates the negative effect a setup has on NT vis-à-vis the unweighted average across the MPS methods, whereas GM15 diminishes the negative effect a setup has on NT vis-à-vis the unweighted average across the MPS methods. This result can be seen in Figure 6. However, the steep negative slopes in all instances indicate the severe detrimental impact Setup has on NT. From a practical perspective, setup operations can make the planning process complex and we expect further throughput deviation from the initial MPS. Among MPS models in the literature, GM15 method considered the role of setup operations as part of MPS development. From a statistical standpoint, it is straightforward to have the MPS method can moderate the impact of setup requirements on NT. We can conceptualize setup as a "between-scenario" measure in that it is fixed in the 64 scenarios (which we also term test problems), whereas the MPS method is a "within-scenario" measure in that it varies within each scenario. Thus, this is conceptually equivalent to testing a cross-level interaction (Singer and Willett, 2003) between a "level-2" predictor (setup) and a "level-1" predictor (the vector of categorical variables capturing the different MPS methods).

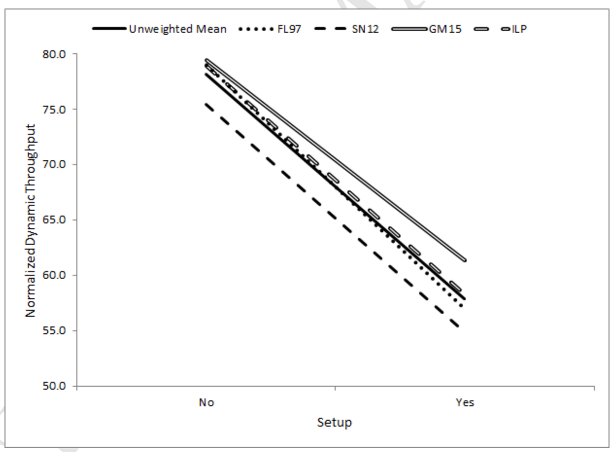

Figure 6: Plot of the Predicted NT for the Interaction between Setup and the MPS Methods

6. Concluding Remarks and Managerial Implications

In this paper, we investigated the predictability of throughput in complex job shop systems at an aggregate level and before the MPS development stage. More specifically, we addressed two research questions regarding the practicality of accurately predicting throughput in job shop systems, the factors that influence the actual throughput and the factors that moderate the throughput. The results indicated that accurately predicting throughput based on problem characteristics is feasible. The mixed-effects model performed very well, with an R^2 of 0.756 based on a sample of 192 observed cases. Our validation using an independent sample of 64 cases confirmed the accuracy of the prediction model with $R^2 = 0.733$, suggesting the model captures the fundamental factors that affect NT. The results indicate that the AutoCase and HC98 problems had higher NT in comparison with AC02. We also identified that Setup is a major factor that negatively affects realized throughput. The problems with setup had, on average, 21.87% less NT compared to their counterparts without setup. The MPS methods are found to influence the NT. The GM15 algorithm resulted, on average, in higher NT compared to the other MPS methods examined in this research.

In response to the second research question, we find that the impact of four out of six problem characteristics (identified in Section 3.2) on NT are moderated by the MPS methods. The characteristics include the RCM, CapacityShortage, RUCM, and Setup. Furthermore, we observed that SN12's performance relative to the unweighted average across the four MPS methods declines when there is a capacity shortage. In contrast, GM15 performs better than the unweighted average across the MPS methods when there is a capacity shortage. The interaction between the RUCM and GM15 being statistically significant and positive indicates that the positive effect of RUCM on NT is more pronounced when GM15 is utilized. The final significant set of interactions terms involves Setup, which indicates that FL97 exacerbates the negative effect setup requirements has on NT, whereas GM15 diminishes the negative effect setup requirements has on NT.

The results of this research have practical implications for production planners and marketing managers of manufacturing companies. They can increase accuracy of their predicted throughput by choosing the most appropriate MPS method based on problem characteristics. Managers should pay attention to the sensitivity level and capabilities of scheduling tools. If demands require complex operations or processes, the tools with a proven record of performance evaluation in a static situation can be very misleading. In a static situation, the role of factors in scheduling, such as WIP, queues, setup time, and sequence of operations, is usually ignored. Therefore, tools such as ILP for complex operations may not be enticing. However, it can be suitable for simple operations flow. In sum, checking the type of required input variables (e.g., setup times) for managers can be helpful for selecting scheduling tools or the level of confidence in the throughput estimate.

The findings of this research should be interpreted considering its limitations. Our results are based on a real case from the auto industry and two of the most complex scheduling problems from the literature. Although these could represent a wide range of scheduling problems, care should be taken in generalizing the findings to problems with significantly different characteristics. Moreover, we used simulation to estimate the dynamic throughput after the implementation of detailed schedules at shop floor. As such, the general limitations of simulation modeling would be applicable to our research. This research can be extended in a number of ways. First, inclusion of more problem characteristics could be examined to enhance the accuracy of throughput predictions for different industries. Next, the role of bill-of-material (BOM) and dependence on suppliers could be considered influential factors for companies with very large BOMs and numerous suppliers. Moreover, understanding the impact of unbalanced levels of complexity would be an interesting research subject. For instance, if complexity occurs mainly because several setup operations are involved instead of because of the sequence of operations or the level of capacity shortage, what would be the best options to make accurate predictions? Finally, the effect of the detailed scheduling method on NT could be verified in future research.

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Electronic Supplement

Appendix A. List of Acronyms

Table A1: List of Acronyms

Acronym	Definition
MPS :	Master Production Scheduling
CNC :	Computer Numerical Controlled
BOM :	Bill-of-Material
WIP :	Work-in-Process
MVA :	Mean Value Analysis
ARMA :	Autoregressive Moving Average
T :	Throughput
NT :	Normalized Throughput
AutoCase :	The Auto Case
HC98 :	The case problem introduced by Hsu and Chung (1998)
AC02 :	The case problem introduced by Atwater and Chakravorty (2002)
ComplexityLevel :	Complexity Level
RCM :	Ratio of Complex Machines
DPMIM :	Density of Part-Machine Incidence Matrix
CapacityShortage :	Capacity Shortage
RUCM :	Ratio of Under-Capacituy Machines
Setup :	Setup requirement
ILP :	Integer Lindear Programming
FL97 :	The MPS method proposed by Fredendall and Lea (1997)
SN12 :	The MPS method proposed by Sobreiro and Nagano (2012)
GM15 :	The MPS method proposed by Golmohammadi and Mansouri (2015)

Appendix B. Additional Data for the AutoCase Problem

Table B1: Processing and Setup Times of Operations for Products A and C (minutes)

Product A			Product C		
Machine	Processing time (Mean, Std. Dev.)	Setup time (Mean,Std. Dev.)	Machine	Processing time (Mean, Std. Dev.)	Setup time (Mean,Std. Dev.)
M8	Normal (0.5, 0.14)	Gamma (20,5)	M9	Normal (0.5, 0.13)	Gamma (16,7)
M7	Normal (0.5, 0.19)	Gamma (122,24)	M12	Normal (1.35, 0.28)	Gamma (22,9)
M7	Normal (1.5, 0.23)	Gamma (115,36)	M4	Normal (0.5, 0.19)	Gamma (30,11)
M3	Normal (1, 0.25)	Gamma (27,5)	M6	Normal (0.85, 0.23)	Gamma (47,22)
M5	Normal (0.5, 0.11)	Gamma (32,8)	M6	Normal (0.75, 0.31)	Gamma (42,19)
M3	Normal (0.5, 0.21)	Gamma (37,15)	M12	Normal (2, 0.71)	Gamma (48,24)
M5	Normal (0.5, 0.12)	Gamma (26,11)	M16	Normal (0.3, 0.1)	Gamma (28,12)
M4	Normal (0.5, 0.21)	Gamma (33,14)	M6	Normal (1, 0.39)	Gamma (46,18)
M4	Normal (0.5, 0.17)	Gamma (20,5)	M12	Normal (1.4, 0.17)	Gamma (22,9)
M5	Normal (0.5, 0.22)	Gamma (20,5)	M13	Normal (4, 1.6)	Gamma (32,15)
M2	Normal (0.4, 0.11)	Gamma (20,5)	M13	Normal (5,1.9)	Gamma (29,13)
M2	Normal (0.5, 0.15)	Gamma (20,5)	M14	Normal (2, 0.8)	Gamma (126,46)
M7	Normal (1, 0.27)	Gamma (132,29)	M15	Normal (1, 0.37)	Gamma (64,34)
M7	Normal (1, 0.32)	Gamma (112,44)	M16	Normal (0.3, 0.12)	Gamma (35,10)

Table B2: Processing and Setup Times of Operations for Products B1 and B2 (minutes)

Product B1			Product B2		
Machine	Processing time (Mean, Std. Dev.)	Setup time (Mean,Std. Dev.)	Machine	Processing time (Mean, Std. Dev.)	Setup time (Mean,Std. Dev.)
M1	Normal (0.25, 0.11)	Gamma (22,6)	M9	Normal (0.5, 0.12)	Gamma (17,5)
M5	Normal (0.3, 0.16)	Gamma (33,10)	M12	Normal (1.25, 0.26)	Gamma (22,8)
M6	Normal (0.5, 0.15)	Gamma (51,19)	M4	Normal (0.4, 0.15)	Gamma (35,7)
M5	Normal (1, 0.21)	Gamma (30,8)			
M5	Normal (0.45, 0.19)	Gamma (30,14)			
M4	Normal (0.3, 0.14)	Gamma (45,17)			
M6	Normal (0.5, 0.15)	Gamma (80,13)			
M5	Normal (0.55, 0.13)	Gamma (30,5)			
M4	Normal (0.3, 0.11)	Gamma (32,9)			
M3	Normal (1, 0.27)	Gamma (28,11)			
M1	Normal (1.05, 0.31)	Gamma (33,14)			
M10	Normal (0.5, 0.17)	Gamma (55,16)			
M11	Normal (3, 0.51)	Gamma (31,10)			

Table B3: Processing and Setup Times of Operations for Products D and E (minutes)

Product D			Product E		
Machine	Processing time (Mean, Std. Dev.)	Setup time (Mean,Std. Dev.)	Machine	Processing time (Mean, Std. Dev.)	Setup time (Mean,Std. Dev.)
M1	Normal (1, 0.11)	Gamma (14,3)	M1	Normal (0.5, 0.1)	Gamma (13,3)
M2	Normal (2, 0.13)	Gamma (15,6)	M4	Normal (0.5, 0.1)	Gamma (20,5)
M4	Normal (0.3, 0.09)	Gamma (20,10)	M5	Normal (0.5, 0.06)	Gamma (35,10)
M5	Normal (1, 0.23)	Gamma (30,12)	M4	Normal (1, 0.08)	Gamma (37,20)
M4	Normal (0.2, 0.11)	Gamma (22,5)	M5	Normal (0.5, 0.1)	Gamma (32,10)
M5	Normal (1, 0.21)	Gamma (28,4)	M4	Normal (0.5, 0.1)	Gamma (20,9)
M7	Normal (0.75, 0.12)	Gamma (31,8)	M6	Normal (1, 0.12)	Gamma (30,8)
M8	Normal (2, 0.29)	Gamma (15,3)	M7	Normal (1, 0.09)	Gamma (15,5)
M13	Normal (1, 0.18)	Gamma (21,6)			

Table B4: Aggregate Processing Times and Machine Capacities of the AutoCase (minutes)

Products	Machines																Demand	Contribution margin
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16		
A	0	0.9	1.5	1	1.5	0	4	0.5	0	0	0	0	0	0	0	0	2000	1500
B	1.3	0	1	1	2.3	1	0	0	0.5	0.5	3	0	0	0	0	0	5000	2200
C	0	0	0	0.5	0	2.6	0	0	0.5	0	0	4.75	9	2	1	0.6	2000	3000
D	1	2	0	0.5	2	0	0.75	2	0	0	0	0	1	0	0	0	3000	1700
E	0.5	0	0	2	1	1	1	0	0	0	0	0	0	0	0	0	3000	2800
Available Capacity	6300	17000	8640	15700	24520	13500	10500	16920	7200	3360	20000	11520	21200	4800	2400	1440		
Required Capacity	11000	7800	8000	15500	23500	13200	13250	7000	3500	2500	15000	9500	21000	4000	2000	1200		
Capacity Difference	-4700	9200	640	200	1020	300	-2750	9920	3700	860	5000	2020	200	800	400	240		