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INTEGRATED DECISION MODEL FOR INTERRELATED SUB-PROBLEMS OF PART DESIGN OR SELECTION, MACHINE LOADING AND MACHINING OPTIMIZATION

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ABSTRACT

In the work presented in this paper, we made an attempt to integrate the decisions for interrelated sub-problems of part design or selection, machine loading and machining optimization in a random flexible manufacturing system (FMS). The main purpose was to come up with an optimization model for achieving more generic and consistent decisions for the FMS and which can be practically implemented on the shop floor to help designers and other engineers in several ways, including, for instance, to optimize the designs of parts for specific FMS.

In order to attain the generic decisions, an integer nonlinear programming (INLP) problem was formulated and solved to maximize the FMS throughput. Based on the results, the part design or selection, machine loading and machining optimization decisions can be simultaneously made. To get more insights of the results and also to check the validity of the model, a two-factor full factorial design was implemented for the sensitivity analysis, analysis of variance (ANOVA) and residual analysis. The computational analyses show that the tooling budget and available processing time were both statistically significant to throughput and confirmed that the model is valid with the data normally distributed.

KEYWORDS

Optimization, part design, part selection, machine loading, machining optimization, integer nonlinear programming, flexible manufacturing systems

NOTATIONS:

The following notations were used in the formulation of the decision model:

(1) Indices

$j = 1, \ldots, J$ for part type
$o = 1, \ldots, O_j$ for operation
$t = 1, \ldots, T$ for tool type
$k = 1, \ldots, K$ for machine

(2) Decision variables

$x_{jotk} = 1$, a fraction of operation o of part j to be processed using tool t on machine k
$x_j = 1$, if part type j is selected, 0 otherwise
$y_{tk} = 1$, if tool type t is assigned to machine k, 0 otherwise
v_{jotk} = cutting speed for combination j,o, t, k (m/min)
f_{jotk} = feed rate for combination j,o, t, k (mm/rev or mm/tooth)

(3) Parameters

α_{jt} = tool life constant of the cutting speed for tool t on part j
β_{jt} = tool life constant of the feed rate for tool t on part j
γ_{jt} = tool life constant of the depth of cut for tool t on part j
δ_{jt} = tool life constant of the width of cut in milling operations for tool t on part j
ω_{jt} = tool life constant of the tool diameter in milling operations for tool t on part j
λ_{jt} = tool life constant of the number of tool teeth in milling operations for tool t on part j
A_k = available processing time at machine k (min)
a_{jot} = depth of cut (mm) for operation o on part j using tool t
B = available tooling budget ($)
C_t = cost per edge ($) of tool t
D_{jo} = tool diameter (mm) for operation o on part j
E_{jt} = tool life constant for tool t on part j
F^L_{jotk} = lower feed rate limit for combination j,o, t, k (mm/rev or mm/tooth)
F^U_{jotk} = upper feed rate limit for combination j,o, t, k (mm/rev or mm/tooth)

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G_k = number of slots on the tool magazine of the machine k
T_{jt} = Tool life for part j and tool t combination
L_{jo} = length of cut (mm) for operation o on part j
M_{jot}, N_{jot} = machining constants for operation o on part j using tool t
Q_j = production quantity of part type j
R_t = replacement time for tool t (min)
S_t = number of slots required by tool type t
u_j = value coefficient of part type j
V^L_{jotk} = lower cutting speed limit for combination j,o, t, k (m/min)
V^U_{jotk} = upper cutting speed limit for combination j,o, t, k (m/min)
W_j = width of cut on part j (mm)
Z_t = number of teeth of the tool t

INTRODUCTION

The concept of flexible manufacturing systems (FMSs) emerged in order to offer rapid response to market demands and provide competitive advantage. FMSs have substantial benefits including increased machine utilization, less number of machines, reduced floor space, greater responsiveness to change, reduced inventory requirements, lower manufacturing lead times, and higher labor productivity. To gain these benefits, FMSs are designed to operate with highly computer-numerically controlled (CNC) machine tools, interconnected by automated material handling and storage systems all interfaced via a central computer. FMSs are classified as being either dedicated or random. In dedicated-FMS types, the system is designed to produce a smaller family of similar parts with a known and limited variety of processing requirements. In random-FMS types, the system is capable of producing a larger family of parts having a wide range of configurations using various processing sequences.

Decision making during the production planning is the essential key for effective FMS. Among the FMS production planning problems defined by Stecke [1] that should be solved prior to setting the FMS into operation include: part type selection, machine grouping, machine loading, production ratio, and resource allocation problems. Liang [2] reported that, of these planning problems, part selection and machine loading are more important in the FMS such that they have attracted many researchers. However, the decisions of part design or selection and machine loading problems are not effective because the values of machining parameters such as cutting speed, feed rate and depth of cut are often predetermined and not optimized during FMS planning. Tolouei-Rad and Bidhendi [3] emphasized the necessity for optimizing the machining parameters for effective utilization of machine tools on the manufacturing shop floor. Since FMSs mostly involve machining processes using the CNC machining centers which are rather expensive, it is extremely important to optimize the machining parameters during FMS planning in order to operate the CNC machine tools more effectively.

This study is aimed at formulating and solving a combined problem of part design or selection, machine loading and machining optimization in a random FMS in order to obtain generic and more effective decisions while improving the performance. An integer nonlinear programming (INLP) was therefore formulated to represent the combined part design or selection, machine loading and machining optimization problem. The objective of the model was to maximize the throughput of the FMS so that many parts can be produced within the limitations of the production resources. The test data for the model were obtained from the literature and the model was solved using LINGO nonlinear programming software. A sensitivity analysis was performed through computational experiments in order to get more insights of the results. ANOVA tests were used to determine the significance of the production resources such as tooling budget and available processing time on the throughput. A residual analysis was used to check the validity of the model and the consistency of data.

STATE OF THE ART OVERVIEW AND PROBLEM DEFINITION

Many studies have dealt with FMS planning problems, chiefly the part design or selection and machine loading problems. Part design or selection is the problem of designing or selecting part types for simultaneous processing of parts while the FMS performance is optimized. Machine loading problems are concerned with the optimum allocation of part operations and required tools amongst the machines in the FMS with a given part-mix in a production horizon. Part design or selection and machine loading problems have been solved using either heuristics methods, mathematical programming techniques, artificial intelligent (AI)-based approach, or a combination of mathematical programming techniques and AI-based approach. Computer software such as LINDO, GAMS have been very useful in solving related linear and integer programming problems.

The part selection methods proposed by Kusiak [4] emphasized selecting similar parts using several similarity measures and associated clustering and heuristic methods. These methods however ignored the constraints of production resources that are present in the part selection problem. Ram *et al.* [5] introduced a methodology for modeling the machine loading and tool allocation problem to provide a wide application to the design and operation of the FMS. The computer code was developed to handle incompatibility between operations and machines and operations and tools.

Srivastava and Chen [6] addressed the part type selection problem as a 0-1 integer programming model and partitioned the given production order of part types into batches that can be processed with the limited production resources such as capacity of the tool magazine, pallets, fixtures and available machine time. Vidyarthi and Tiwari [7] suggested a fuzzy-based solution methodology to solve a machine-loading problem for the purpose of minimizing system unbalance and maximizing the throughput, whereas the system technological constraints on the availability of machining time and tool slots were posed. The determination of job ordering and job sequencing before loading was carried out by evaluating the contribution of each

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job to its characteristics such as batch size and processing time.

Jang *et al.* [8] showed that a machine-loading problem can be formulated as a combinatorial problem within a flexible manufacturing cell (FMC) environment, and applied Hopfield Networks to balance the workload of the machines. Choudhary *et al.* [9] modeled a combined part selection and machine loading problem with consideration of several technological constraints related to the flexibility of machines, availability of machining time, tool slots, etc., while aiming at satisfying the objectives of minimizing the system unbalance, maximizing throughput, and achieving a better overall FMS utilization. More recently, Prakash *et al.* [10] came up with a more effective immune algorithm to ease the tedious computations of machine loading problems in the FMS. The proposed algorithm was tested using different data sets and proven to reduce computational complexity.

Studies on the optimization of machining parameters have been widely covered in the literature. The optimization of machining parameters is the determination of optimum machining parameters such as cutting speed, feed rate and depth of cut to achieve high machining efficiency. The approach to solving machining optimization problems involves the use of various techniques including mathematical programming, fuzzy logic, genetic algorithm, simulated annealing, and expert systems. Since most of machining optimization problems are nonlinear in nature, computer software such as LINGO, GINO and GAMS are commercially available, and have continued to be more useful in solving different nonlinear optimization problems.

Petropoulos [11] performed a study on the determination of optimum cutting speed and feed using a minimum-production-cost criterion with consideration of machining restrictions such as machining power and surface roughness in a single machine using geometric programming. Ermer and Kromodihardjo [12] evaluated the economical benefits of multi-pass cutting operations and single-pass cutting when the practical cutting constraints such as cutting force and cutting power are included in the optimization problem. The results from their work showed that double-pass and triple-pass cutting operations may be more preferred than a single-pass operation when the problem is treated with cutting constraints.

Agapiou [13] conducted a study on the optimization of multi-stage machining systems to reduce the values of machining parameters in order to minimize the cost at workstations while utilizing the idle time to the full extent at all processing machines and balance the machining system. An analytical mathematical method and a computational algorithm were developed to solve the proposed optimization model. Saravan *et al.* [14] outlined various optimization procedures for solving a CNC turning problem to determine the optimum operating parameters such as cutting speed and feed rate. The total production time was considered as the objective function, subject to constraints such as cutting force, power, tool-chip interface temperature and surface roughness of a product.

Alberti *et al.* [15] designed a system for optimizing the cutting parameters in both conventional milling and high-speed milling while reducing the processing time and ensuring optimal finishing conditions. The designed system helped to make better decisions on the optimal machining parameters than the decisions obtained using experience or handbooks. Zhang *et al.* [16] developed a mixed integer evolutionary algorithm based on genetic algorithm to solve machining optimization problems. The algorithm demonstrated to have higher performance and computational efficiency for solving non-linear machining optimization problem. Lately, Manna and Salodkar [17] described a procedure to obtain optimum machining parameters for a turning operation using dynamic programming for a minimum unit cost of production. A Taguchi method was used to determine better machining parameters to achieve superior surface finish. A multiple linear regression analysis was conducted to establish a mathematical model that relates machining parameters and surface roughness of a part.

Although the sub-problems of part design or selection, machine loading, and machining optimization have common production resources such as the available processing time, their decisions are often made separately during the planning stage. For example, most of the studies on FMS planning problems tend to base on pre-specified values of machining parameters. This tendency hinders the effective utilization of the machines in the FMS because the machines may be operated at lower cutting speed resulting in lower productivity or at higher cutting speed leading to higher machining cost. It was therefore imperative to incorporate the determination of machining parameters in FMS planning so as to obtain generic and effective decisions which can be practically implemented on the manufacturing shop floor while improving the FMS performance.

FORMULATION OF THE INTEGRATED MODEL

A combined decision model for three interrelated sub-problems of part design or selection, machine loading and machining optimization was formulated as an integer nonlinear programming (INLP) problem. The model parameters are assumed to be deterministic and static. The objective of the model was to maximize the FMS throughput within the boundaries of the operational requirements. Shanker and Srinivasulu [18] signified that the maximum throughput is a primary objective for the FMS. The integrated decision model for maximizing the FMS throughput was formulated as follows.

$$\text{Maximize } \sum_{j=1}^{J} u_j Q_j x_j \tag{1}$$

Subject to:

$$\sum_{t=1}^{T}\sum_{k=1}^{K} x_{jotk} = x_j, \ \forall j, o \tag{2}$$

$$\sum_{j=1}^{J}\sum_{o=1}^{O_j}\sum_{t=1}^{T} x_{jotk} \geq 1, \ \forall k \tag{3}$$

$$\sum_{o=1}^{O_j}\sum_{t=1}^{T} x_{jotk} \leq 1, \ \forall j, k \tag{4}$$

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$$\sum_{j=1}^{J}\sum_{o=1}^{O_j} x_{jotk} \le y_{tk}, \forall t, k \quad (5)$$

$$\sum_{t=1}^{T} S_t y_{tk} \le G_k, \forall k \quad (6)$$

$$\sum_{j=1}^{J}\sum_{o=1}^{O_j}\sum_{t=1}^{T}\left(N_{jot} v_{jotk}^{-1} f_{jotk}^{-1} + M_{jot} v_{jotk}^{\alpha_{jt}-1} f_{jotk}^{\beta_{jt}-1} R_t\right) Q_j x_{jotk} \le A_k, \forall k \quad (7)$$

$$\sum_{j=1}^{J}\sum_{o=1}^{O_j}\sum_{t=1}^{T}\sum_{k=1}^{K} M_{jot} v_{jotk}^{\alpha_{jt}-1} f_{jotk}^{\beta_{jt}-1} C_t Q_j S_t y_{tk} \le B \quad (8)$$

$$V_{jotk}^{L} \le v_{jotk} \le V_{jotk}^{U}, \forall j, o, t, k \quad (9)$$

$$F_{jotk}^{L} \le f_{jotk} \le F_{jotk}^{U}, \forall j, o, t, k \quad (10)$$

$$x_{jotk} = 0 \text{ or } 1, \forall j, o, t, k \quad (11)$$

$$x_j = 0 \text{ or } 1, \forall j \quad (12)$$

$$y_{tk} = 0 \text{ or } 1, \forall t, k \quad (13)$$

The decisions of the integrated part design or selection, machine loading (operation allocation and tool assignment) and machining optimization (optimal cutting speed and feed rate) problem will be obtained when the INLP model is solved. The objective function (1) maximizes the FMS throughput. The value coefficient u_j may represent the dollar or due-date value of the part type. Constraint (2) states that the total proportion of a part processed at all alternative machines using all feasible tools should be the same for all operations, either 0 or 1. To avoid the starvation of machines and ensure that all machines are utilized in the shop floor, Constraint (3) binds every machine to perform at least one operation on a part. Constraint (4) disallows the recirculation of parts on machines. Constraint (5) ensures that if a part is allocated to a machine, the required tool should be assigned to that machine. The capacity of tool magazine is restricted by constraint (6). Constraint (7) forces the total processing time at each machine not to exceed the available processing time in the shop floor. Constraint (8) assures that the total tooling cost is not beyond the available tooling budget. Constraints (9) and (10) give the lower and upper bounds for cutting speed and feed rate respectively. Constraints (11) through (13) represent binary restrictions on the decision variables.

The total processing time is the sum of the machining time and tool replacement time. The first term in Constraint (7) is the machining time and the second term is the tool replacement time. Machining time is the actual time required to process the part on a machine and is given by:

$$N_{jot} v_{jotk}^{-1} f_{jotk}^{-1} \quad (14)$$

where N_{jot} is a machining constant known as:

$$N_{jot} = \frac{\pi D_{jot} L_{jo}}{1000}, \text{ for turning, boring, drilling, tapping or reaming operations,} \quad (15)$$

and

$$N_{jot} = \frac{\pi D_{jot} L_{jo}}{1000 Z_t} \text{ for milling operations.} \quad (16)$$

Tool replacement time is the time needed to remove a worn tool from the machine and replace with a new tool. The total tooling cost in Constraint (8) is the cost of purchasing new tools. Both the tool replacement time and tooling cost are functions of the Taylor's tool life equation. The extended tool life equation reported by Lambert and Walvekar [19] can be written in the following form:

$$T_{jt} = \frac{E_{jt}}{v_{jotk}^{\alpha_{jt}} f_{jotk}^{\beta_{jt}} a_{jot}^{\gamma_{jt}}} \quad (17)$$

The tool replacement time and tooling cost can therefore respectively be presented as:

$$M_{jot} v_{jotk}^{\alpha_{jt}-1} f_{jotk}^{\beta_{jt}-1} R_t, \quad (18)$$

and

$$M_{jot} v_{jotk}^{\alpha_{jt}-1} f_{jotk}^{\beta_{jt}-1} C_t \quad (19)$$

where M_{jot} is a machining constant which is defined by Wang and Liang (2005) as:

$$M_{jot} = \frac{\pi D_{jot}^{1-\omega_{jt}} L_{jo}}{1000 E_{jt}} \text{ for drilling operations;} \quad (20)$$

$$M_{jot} = \frac{\pi D_{jot}^{1-\omega_{jt}} L_{jo} a_{jot}^{\gamma_{jt}}}{1000 E_{jt}} \text{ for reaming/tapping operations;} \quad (21)$$

and

$$M_{jot} = \frac{\pi D_{jot} L_{jo} a_{jot}^{\gamma_{jt}}}{1000 E_{jt}} \text{ for turning/boring operations.} \quad (22)$$

Shnumugam *et al.* (2000) and Wang and Liang (2005) defined the machining constant

$$M_{jot} = \frac{\pi D_{jot}^{1-\omega_{jt}} L_{jo} a_{jot}^{\gamma_{jt}} W_j^{\delta_{jt}} Z_t^{\lambda_{jt}-1}}{1000 E_{jt}} \text{ for milling operations.} \quad (23)$$

RESULTS AND DISCUSSIONS

The FMS under consideration has 4 CNC machining centers, each with a tool magazine capacity of 10 tool slots. 20 types of tools are available, and the number of slots needed by each tool set is given. The tool replacement time is estimated to be 1 min. The tool-operation and tool-machine compatibilities are pre-specified. There are 10 types of parts waiting for immediate and simultaneous processing in the FMS. The production quantities of the ten types of parts are: 450, 900, 480, 1300, 2000, 700, 1500, 2500, 1000 and 850 respectively. Part types have equal value coefficient=1.

Part and tool data including part and tool materials, operation types, tool costs per edge, tool slot requirements and tool life constants for cutting speeds and feed rates are presented in Table 1. Tool life constants were taken from Shnumugam *et al.* [20] and Wang and Liang [21] while the tool costs per edge were obtained from McMaster-Carr Supply

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Company [22]. Machining data which incorporate tool sizes, number of tool teeth, machining length, width and depth and related constants are given in Table 2. The recommended limits of cutting speeds and feed rates were found in Modern Machine Shop's Handbook [23] and are listed in Table 3.

The analyses were carried out using Extended LINGO software Release 11 which can handle unlimited number of linear and nonlinear constraints as well as unlimited number of integer, nonlinear and global variables (LINDO Systems Inc., [24]). The model had a total of 384 constraints, 5 of which were nonlinear constraints. The number of nonlinear variables was 250 and integer variables 120. The computation was conducted on Intel Core Duo 2 GHz CPU with 3 GB of RAM memory and the runtime for the problem was 2.1 min.

The results for the available processing time=2880 min and tooling budget=$15,000 are summarized in Table 4 and show that part design or selection, machine loading and machining optimization decisions can be simultaneously made. Part selection was defined by the variable x_j=1. Selected parts for the next production period were 1, 5, 7, 8, and 10 with FMS throughput of 7300. Not all parts could be selected for processing and not all tools could be assigned to machines. This is because of the limited production resources such as the available processing time, the capacity of tool magazine and the tooling budget. The machine loading decision was related to the operation allocation x_{jotk}=1 and tool assignment y_{tk}=1. For example, x_{1124}=1, means that operation 1 of part 1 will be processed on machine 4 using tool type 2. Similarly, y_{24}=1, means that tool 2 is assigned to machine 4. The optimum machining parameters were indicated by v_{jotk} for cutting speed and f_{jotk} for feed rate. For example, v_{1124}=91 m/min and f_{1124}=0.3 mm/tooth are the respective cutting speed and feed rate for operation 1 of part 1 on machine 4 using tool type 2.

Part routes onto the machines were obtained as follows. Part 1: Machine 4 →Machine 2→Machine 3; Part 5: Machine 1→Machine 4; Part 7: Machine 3→Machine 2; Part 8: Machine 3→Machine 1; and Part 10: Machine 1→Machine 2. The workloads in the FMS were well balanced with each machine spending all the available processing time of 2880 min. The magazine tool slots in the machines were not fully used. The number of slots used in Machine 1=3; Machine 2=5; Machine 3=7; and Machine 4=4. This is only 47.5% average tool magazine usage. With lower tool magazine usage, it refers that few cutting tools are used which means a maximum throughput of the FMS can be attained at lower total tooling cost. However, the tooling cost and the penalty cost due to unused tool slots can be compromised basing on the economical benefits that suit the needs of a particular FMS.

The computation for the available processing time=1440 min and tooling budget=$10,000 provide the selected parts 1, 3 and 10 with the maximum throughput of 1780. In this case, the workloads in the FMS were not balanced with Machine 2 spending 1333 min while the rest machines spending all the available processing time of 1440 min to accomplish the assigned operations. Shanker and Srinivasulu [18] pointed out that maximizing throughput in the FMS often leads to unbalanced workload. The reason for unbalanced workload could be that the parts had different processing requirements including the differences in their machining operations, cutting tools, and machining parameters. However, computations in this study have revealed that, when machining parameters are optimized with the part design or selection and machine loading problems, they adjust within their allowable limits and in many cases have provided balanced workloads in the FMS.

To get more insights of throughput results, a sensitivity analysis was conducted. By adopting a two-full factorial design with available processing time and tooling budget factors, each factor assigned to 5 levels, a total of 5×5=25 experiments were run. Figure 1 and Figure 2 explore the fact that increasing the tooling budget or processing time leads to increased throughput. Using the results from computational experiments, ANOVA tests and residual analysis were conducted. ANOVA output in Table 5 shows that the available processing time and tooling budget are both significant to throughput at 99% level, and the available processing time has more effect than tooling budget. A quantile-quantile (Q-Q) plot of residuals in Figure 3 shows that the plot points lie close to a line with a unit slope which is an indication that the data conform to the normal probability distribution and that the model is valid.

CONCLUSIONS AND FUTURE WORK

An integrated decision model was formulated and solved for the purpose of maximizing the throughput of the FMS for specific part configurations. The model represented the combined part design or selection, machine loading and machining optimization problem. The computational results showed that the decisions of sub-problems of part design or selection, machine loading and machining optimization can be concurrently made while improving the FMS performance.

It was observed that tool magazine usage was low which implies lower total tooling cost. But, better utilization of the tool magazine requires tool slots to be loaded as densely as possible. A compromise between tooling cost and penalty cost due to unused tool slots can be found to suit the FMS requirements. In many cases, workloads in the FMS were balanced indicating that optimizing machining parameters with part design or selection and machine loading problems could considerably assist in balancing the workloads in the FMS. The sensitivity analysis and ANOVA tests showed that both tooling budget and available processing time have significant effect on the throughput. The residual analysis confirmed that the model and data were consistent with the data conforming to the normal probability distribution.

The formulated optimization model provides more generic and effective decisions for the FMS which can be practically implemented on the shop floor. It can help designers and other engineers in several ways, including, for instance, to optimize the designs of parts for specific FMS. Although part routes were also determined, it was not exemplified on how the parts could be scheduled onto the machines in the FMS. The next stage of the study will be to make an attempt to optimally schedule the parts in the FMS while minimizing the makespan.

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Table 1: Part and Tool Data

Part Type	Operation Number	Tool Type	Part Material	Operation Type	Tool Material	C_t	S_t	α_{jt}	β_{jt}
1	1	1	Gray Cast Iron	Face Milling	Carbide	315	3	3.12	1.09
		2			Carbide	325	3	3.12	1.09
	2	3		Shoulder Milling	Carbide	210	1	3.12	1.09
		4			Carbide	220	1	3.12	1.09
	3	5		Drilling	Carbide	60	2	2.50	1.25
2	1	6	Carbon Steel	Profile Milling	HSS	40	2	3.03	1.51
		7			HSS	80	2	3.03	1.51
	2	8		Pocket Milling	HSS	25	4	3.03	1.51
		9			HSS	35	4	3.03	1.51
	3	10		Slot Milling	HSS	20	1	3.03	1.51
3	1	1	Gray Cast Iron	Face Milling	Carbide	315	3	3.12	1.09
		2			Carbide	325	3	3.12	1.09
	2	11		Drilling	Carbide	25	1	2.50	1.25
	3	12		Tapping	HSS	30	1	3.33	1.67
4	1	6	Carbon Steel	Profile Milling	HSS	40	2	3.03	1.51
		7			HSS	80	2	3.03	1.51
	2	13		Slot Milling	HSS	15	2	3.03	1.51
5	1	14	Gray Cast Iron	Drilling	Carbide	90	1	2.50	1.25
	2	15		Reaming	HSS	140	1	3.33	1.67
6	1	1	Gray Cast Iron	Face Milling	Carbide	315	3	3.12	1.09
		2			Carbide	325	3	3.12	1.09
	2	5		Drilling	Carbide	60	2	2.50	1.25
	3	16		Reaming	HSS	75	1	3.33	1.67
7	1	8	Carbon Steel	Pocket Milling	HSS	25	4	3.03	1.51
		9			HSS	35	4	3.03	1.51
	2	13		Slot Milling	HSS	15	2	3.03	1.51
8	1	17	Gray Cast Iron	Drilling	Carbide	85	1	2.50	1.25
	2	18		Tapping	HSS	160	1	3.33	1.67
9	1	6	Carbon Steel	Profile Milling	HSS	40	2	3.03	1.51
		7			HSS	80	2	3.03	1.51
	2	8		Pocket Milling	HSS	25	4	3.03	1.51
		9			HSS	35	4	3.03	1.51
10	1	19	Gray Cast Iron	Shoulder Milling	Carbide	235	1	3.12	1.09
		20			Carbide	245	1	3.12	1.09
	2	5		Drilling	Carbide	60	2	2.50	1.25

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Table 2: Machining Data and Constants

Part	Operation	Tool	D_{jot}	Z_t	γ_{jt}	δ_{jt}	ω_{jt}	λ_{jt}	E_{jt}	W_j	L_{jo}	a_{jot}	N_{jot}	M_{jot}
1	1	1	75	5	0.47	0.62	0.62	0	1.62E+08	68	540	5	25.45	3.15E-07
		2	90	5	0.47	0.62	0.62	0	1.62E+08	68	540	5	30.54	3.37E-07
	2	3	30	4	0.47	0.62	0.62	0	1.62E+08	26	180	8	4.24	6.36E-08
		4	40	4	0.47	0.62	0.62	0	1.62E+08	26	180	8	5.65	7.10E-08
	3	5	26	2			1.25		11640		32		2.61	3.82E-06
2	1	6	25	4	1.51	0.3	1.36	0.3	148880	20	600	10	11.78	1.20E-04
		7	30	6	1.51	0.3	1.36	0.3	148880	20	600	10	9.42	8.44E-05
	2	8	16	4	1.51	0.3	1.36	0.3	148880	12	105	10	1.32	2.11E-05
		9	20	4	1.51	0.3	1.36	0.3	148880	12	105	10	1.65	1.95E-05
	3	10	12	2	1.51	0.3	1.36	0.3	148880	12	80	5	1.51	1.02E-05
3	1	1	75	5	0.47	0.62	0.62	0	1.62E+08	68	630	4	29.69	3.31E-07
		2	90	5	0.47	0.62	0.62	0	1.62E+08	68	630	4	35.63	3.54E-07
	2	11	10.2	2			1.25		11640		45		1.44	6.80E-06
	3	12	12		0.33		0.67		7774		45	0.9	1.70	3.99E-05
4	1	6	25	4	1.51	0.3	1.36	0.3	148880	20	500	8	9.82	7.12E-05
		7	30	6	1.51	0.3	1.36	0.3	148880	20	500	8	7.85	5.02E-05
	2	13	10	2	1.51	0.3	1.36	0.3	148880	10	210	6	3.30	3.55E-05
5	1	14	38	2			1.25		11640		50		5.97	5.44E-06
	2	15	39		0.33		0.67		7774		50	0.5	6.13	6.77E-05
6	1	1	75	5	0.47	0.62	0.62	0	1.62E+08	68	280	2.5	13.19	1.18E-07
		2	90	5	0.47	0.62	0.62	0	1.62E+08	68	280	2.5	15.83	1.26E-07
	2	5	26	2			1.25		11640		80		6.53	9.56E-06
	3	16	27		0.33		0.67		7774		80	0.5	6.79	6.94E-04
7	1	8	16	4	1.51	0.3	1.36	0.3	148880	12	400	3	5.03	1.31E-05
		9	20	4	1.51	0.3	1.36	0.3	148880	12	400	3	6.28	1.20E-05
	2	13	10	2	1.51	0.3	1.36	0.3	148880	10	160	5	2.51	2.06E-05
8	1	17	36	2			1.25		11640		40		4.52	4.41E-06
	2	18	39		0.33		0.67		7774		40	0.75	4.90	4.92E-05
9	1	6	25	4	1.51	0.3	1.36	0.3	148880	20	420	4	8.25	2.10E-05
		7	30	6	1.51	0.3	1.36	0.3	148880	20	420	4	6.60	1.48E-05
	2	8	16	4	1.51	0.3	1.36	0.3	148880	12	360	4	4.52	1.81E-05
		9	20	4	1.51	0.3	1.36	0.3	148880	12	360	4	5.65	1.67E-05
10	1	19	50	4	0.47	0.62	0.62	0	1.62E+08	42	340	3	13.35	1.24E-07
		20	60	4	0.47	0.62	0.62	0	1.62E+08	42	340	3	16.02	1.33E-07
	2	5	26	2			1.25		11640		50		4.08	5.98E-06

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Table 3: Recommended Limits of cutting speeds and Feed Rates

Part	Operation	Tool	V^L_{jot1}	V^L_{jot2}	V^L_{jot3}	V^L_{jot4}	V^U_{jot1}	V^U_{jot2}	V^U_{jot3}	V^U_{jot4}	F^L_{jot1}	F^L_{jot2}	F^L_{jot3}	F^L_{jot4}	F^U_{jot1}	F^U_{jot2}	F^U_{jot3}	F^U_{jot4}
1	1	1	91			91	152			152	0.075			0.075	0.3			0.3
		2	91			91	152			152	0.075			0.075	0.3			0.3
	2	3		91	91			152	152			0.075	0.075			0.3	0.3	
		4		91	91			152	152			0.075	0.075			0.3	0.3	
	3	5		12	12			45	45			0.23	0.23			0.5	0.5	
2	1	6	9			9	30			30	0.102			0.102	0.152			0.152
		7	9			9	30			30	0.102			0.102	0.152			0.152
	2	8		9	9			30	30			0.063	0.063			0.127	0.127	
		9		9	9			30	30			0.063	0.063			0.127	0.127	
	3	10		9	9			30	30			0.038	0.038			0.089	0.089	
3	1	1	91			91	152			152	0.075			0.075	0.3			0.3
		2	91			91	152			152	0.075			0.075	0.3			0.3
	2	11		12	12			45	45			0.13	0.13			0.3	0.3	
	3	12		6	6			19	19			0.15	0.15			0.5	0.5	
4	1	6	9			9	30			30	0.102			0.102	0.152			0.152
		7	9			9	30			30	0.102			0.102	0.152			0.152
	2	13		9	9			30	30			0.038	0.038			0.089	0.089	
5	1	14	12			12	45			45	0.23			0.23	0.5			0.5
	2	15	8			8	15			15	0.25			0.25	0.5			0.5
6	1	1	91			91	152			152	0.075			0.075	0.3			0.3
		2	91			91	152			152	0.075			0.075	0.3			0.3
	2	5		12	12			45	45			0.23	0.23			0.5	0.5	
	3	16	8			8	15			15	0.25			0.25	0.5			0.5
7	1	8		9	9			30	30			0.063	0.063			0.127	0.127	
		9		9	9			30	30			0.063	0.063			0.127	0.127	
	2	13		9	9			30	30			0.038	0.038			0.089	0.089	
8	1	17		12	12			45	45			0.23	0.23			0.5	0.5	
	2	18	6			6	19			19	0.15			0.15	0.5			0.5
9	1	6	9			9	30			30	0.102			0.102	0.152			0.152
		7	9			9	30			30	0.102			0.102	0.152			0.152
	2	8		9	9			30	30			0.063	0.063			0.127	0.127	
		9		9	9			30	30			0.063	0.063			0.127	0.127	
10	1	19	91			91	152			152	0.075			0.075	0.3			0.3
		20	91			91	152			152	0.075			0.075	0.3			0.3
	2	5		12	12			45	45			0.23	0.23			0.5	0.5	

Feed rates for milling operations are in mm/tooth and for other operations are in mm/rev.

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Table 4: Results of the Decision Model

Part *j*	Operation *o*	Tool *t*	Machine *k*	Cutting Speed v_{jotk}	Feed Rate f_{jotk}
1	1	2	4	91	0.3
	2	3	2	91.2	0.187
	3	5	3	44	0.365
5	1	14	1	44.7	0.5
	2	15	4	10.4	0.5
7	1	8	3	28.9	0.114
	2	13	2	29	0.086
8	1	17	3	45	0.5
	2	18	1	13.1	0.5
10	1	19	1	92.2	0.282
	2	5	2	12	0.23

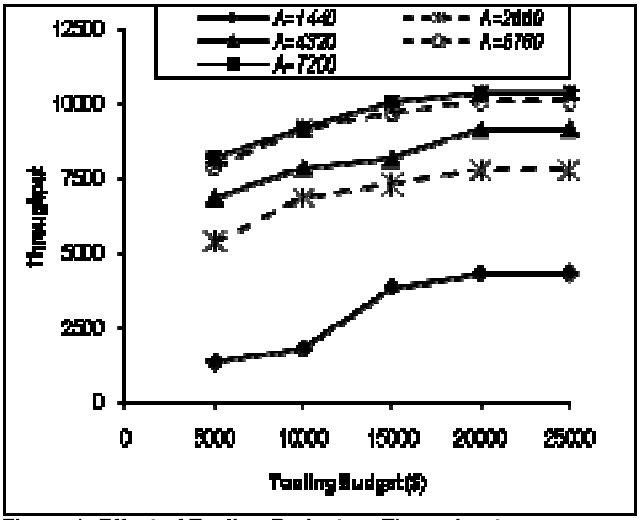


Figure 1: Effect of Tooling Budget on Throughput

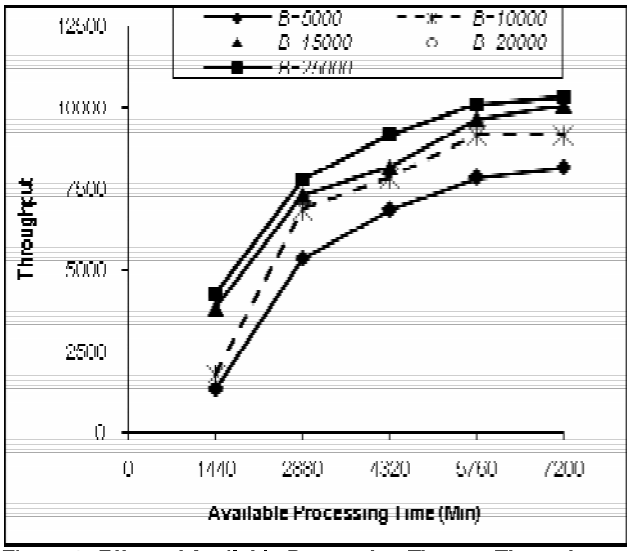


Figure 2: Effect of Available Processing Time on Throughput

Table 5: ANOVA tests for Decision Model

Source of Variation	Sum of Squares	Degree of Freedom	Mean Square	*F*- Computed	*F*- Table
Available time	139968856	4	34992214	341.7	3.01
Tooling budget	21360736	4	5340184	52.1	3.01
Residual	1638504	16	102406.5		
Total	162968096	24			

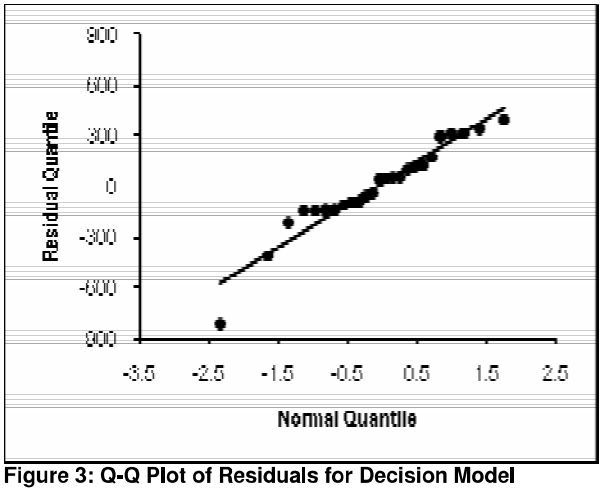


Figure 3: Q-Q Plot of Residuals for Decision Model

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