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CASE STUDY FOR LOT-SIZING PROBLEM IN MTO SUPPLY CHAIN BASED ON SIMULATION OPTIMIZATION APPROACH

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ABSTRACT: *Recently, manufacturers are taking a hybrid approach between MTS and MTO. However, most of literature research on production planning concentrates principally on MTS systems. The MTO area has not received the same degree of attention. There are only some research papers which are based on queueing network models that explicitly talk about the Lot Sizing Problem (LSP) in MTO sector. This paper presents a case study in MTO sector for which analytical model is still extremely complex up to now (multi-stage, multi-product, multi-location, multi-resource with setup, capacity constraints and stochastic demand). The objective is to determine a fixed optimal lot size for each manufacturing product type that will ensure Order Mean Flow Time (OMFT) target value for each finished product type. The adopted approach is carried out in three steps. A Discrete Event Simulation (DES) model was firstly implemented as a tool in estimating (OMFT) performance. Secondly, Design of Experiment is applied to conduct simulation experiments. Finally, a multiple-objective optimization is achieved by applying desirability optimization methodology. The study results illustrate that the LSP in MTO sector is viable and provides a prototype for further research in supply chain co-ordination.*

KEYWORDS: *Lot-Sizing Problem, Make to Order, Discrete Event Simulation, desirability optimization*

1 INTRODUCTION

A supply chain (SC) is a network of facilities and distribution entities such as materials vendors, manufacturers, distributors, wholesalers and retailers that perform the functions of procurement of raw materials, transformation of raw materials into intermediate and finished products and distribution of finished products to customers. A SC is typically characterized by a forward flow of materials and a backward flow of information. End-user demand information suffers from delay and distortion as it moves upstream in a SC. Coordination between organizations in the SC, through sharing of demand information, is a possible solution to counter this distortion. Consequently, enterprises have shown a growing interest for an integrated SC management. An important issue in integrated logistic network management is to control the inventory at different entities while meeting end-customer service level requirements, therefore quantifying the trade-off between inventory investment and end-customer service levels. The dynamic nature of complex logistic chains causes that this trade-off change over time.

The coordination between different entities in the SC is not an easy task, because each one is involved in efforts to reduce costs and maximize profits. However, the various entities may have conflicting objectives, and the profits of the entire SC may suffer if the different stakeholders cannot be brought into agreement and coordinated. Traditional production planning methods, such as material or Manufacturing Requirement Planning (MRP), consider only the availability of materials when organizing demands, and totally ignore such factors as capacity limits and SC configurations. For this reason, MRP cannot provide feasible production plans, since such plans require that capacity limits and multiple objectives be taken into account. To cope with these challenges, Advance Planning and Scheduling (APS) were developed to integrate the planning activities of the entire SC, providing powerful planning procedures and methodologies that are able to react quickly to exceptions and variability.

In addition, each entity of the SC that has the ability to fill customer orders quickly, as well as offer custom products has the benefit of a competitive advantage. However, the need to have high product variety and quick response time places conflicting demands on the production system. It is for this reason that business which competes on response time focuses on producing a limited portfolio of products. Items are produced ahead of demand and kept in stock, ready to be shipped upon receipt of orders. Producing to stock becomes costly when the number of products is large. It is also risky when demand is highly variable and/or products have short life cycles (Hendry and Kingsman, 1989). Therefore, an increasing number of companies have been shifting its production from the make-to-stock (MTS) to the make-to-order (MTO) sector such as Dell, BMW, Compaq, and Gateway (Gunasekaran and Ngai, 2009). Additionally, the thrust in today's manufacturing environment is to move towards Lean manufacturing philosophy. However, most of literature research on MRP and APS approaches concentrates on MTS systems. As a consequence, many researches provide excellent surveys of models and methods for the deterministic and the stochastic demand cases (Karimi et al. 2003). The MTO area has not received the same degree of attention. In particular, there are only a handful of research papers that explicitly talk about the Lot sizing problem (LSP) in MTO sector. In this case, only methods based on queueing theory have been subject to a mathematical analysis of MTO problems.

(Williams, 1984) noted that classical inventory control generally ignores capacity constraints and interactions between products. He considered an M/G/m queuing model that incorporated inventory holding costs, setup costs and backorder costs. Lot sizes and reorder points were treated as the decision variables in cost minimization. As well, Williams addressed the problem of using demand patterns to decide whether to choose MTS or MTO. (Bertrand, 1985) presented a cost minimization model that considered setup costs and both work-in-process and finished goods inventory holding costs. Optimal lot sizes were determined through iteratively estimating lot flow times and then readjusting lot sizes until convergence occurred. Flow time estimation was based on closed queueing network assumptions and the lot size optimization model was based on solving a set of non- linear equations, derived through partial differentiation of the cost function with respect to product lot sizes.

(Dellaert and Melo, 1996) consider a single item capacitated lot-sizing problem motivated by a Dutch manufacturer of steel pipes operating in a MTO environment. The objective is to determine in each period of the planning horizon the optimal size of production lots so that delivery dates are met as closely as possible with a limited number of set-ups. To solve this problem, they propose an exact method based on Markov Decision Process and dynamic programming for small problems. They propose also three heuristic procedures to solve general problems. (Ettl et al. 2000) developed a SC model that takes as input the bill-of-materials, the nominal lead times, the demand and cost data, and the required customer service levels. In return, the model generates the base-stock level at each store, the stocking location for a component or an end-product. They assume a distributed inventory control mechanism whereby each site in the network operates according to a base-stock control policy. This base-stock policy makes authors avoid the consideration on determining the lot sizes at each store. (Srinivasa Raghavan, 2001) presented an analytical method for evaluating the performance of MTO supply chains using general queueing networks. However, they assumed that demand arrivals are deterministic.

(Missbauer, 2002) discussed the need for capacity constrained lot-sizing research including economic factors. He demonstrated the use of M/G/1 lot-sizing relationships which minimize the weighted sum of queue times, setup costs and finished goods holding costs. (Lee et al. 2003) presented a model for computing the parameters of an integrated inventory replenishment and outbound dispatch scheduling policy under dynamic demand considerations. Their model can be applied to MTO supply chain attempt to determine the optimal lot-sizes incorporating shipping costs. (Choi and Enns, 2004) introduced relationships to determine lot sizes that minimize costs for the single and multiple product cases when the production rate is specified. Finally, (Dong and Chen, 2005) presented an analytical modeling framework for integrated logistic chains. They develop a network of inventory-queue models for performance analysis for three cases: base stock policy, batch-ordering policy and for the lot-sizing problem. The validity of their analytical model is illustrated by comparing the results from DES study. However, their framework is used for single product logistic chains and their performance also. Recently, (Liu and Lian, 2009) have considered a two-stage distributed manufacturing system under base stock policy. For modeling, they use a network of inventory-queue model to evaluate the inventory cost and service level achievable for given inventory control policy. For resolution, they derive an algorithm to find the optimal inventory control policy that minimizes the overall inventory holding cost and satisfies the given service level requirements.

The remainder of this paper is organized as follows. Section 2 looks at simulation optimization approach. The adopted metamodel-based simulation optimization approach is presented in Section 3. Then the complete case study description and the corresponding simulation model are shown in section 4. Afterwards, section 5 presents the obtained simulation results and the multiple-objective optimization. Lastly, conclusion is made in Section 6.

2 SIMULATION OPTIMIZATION LITERATURE

The computer simulation is a model or a function that transforms the inputs into the outputs. The operational parameters and their variables are described as the inputs and the performances, which are derived from simulation, are described as the outputs. The operational conditions are then tested on this model to achieve the objectives. One objective of the application of simulation is to search for a set of operational parameters so that system performance is improved. Simulation is essentially a trial-and-error approach. It is a tool for problem solving; by itself, it cannot provide an answer. In addition to a good model, one also needs a sound technique to utilize the information from a simulation to make a decision. One such technique is optimization via simulation.

Simulation optimization provides a structured approach to determine optimal input parameter values, where optimal is measured by a function of output variables associated with a simulation model. Several excellent surveys have been written on this topic. It is an active area in the field of the stochastic optimization. Reviews of the current research on simulation-based optimization developments can be found in (Carson and Maria 1997; Fu 2002; Tekin and Ihsen 2004; Andradottir 2006; Chen et al. 2008). Theses surveys classified the existing techniques according to problem characteristics such as Random search and Metaheuristics approaches, Ranking and Selection, direct and indirect Gradient Estimation and Metamodel methods. (Barton and Meckesheimer 2006) address the theoretical aspect of metamodel based approaches to simulation optimization which will be applied in this work.

A metamodel-based optimization strategy consists of choosing a metamodel form, designing an experiment to fit the metamodel, fitting the metamodel and validating the quality of its fit, optimizing the metamodel (or using it to provide a search direction), and checking the performance of the simulation at the metamodel-predicted optimum (or in the metamodel-determined search direction). In some cases this process is repeated, with the new experiment design focused on the neighbourhood of the predicted optimum. Using metamodel based approach in simulation optimization has many advantages. Response surface models (metamodels) have substantial statistical theory behind them that permit assessment of the uncertainty about the exact value of the optimal design parameter values and the optimal response. Further, the metamodels used during the optimization phase have other usefulness: they can provide insight on the behaviour of the simulated system, sensitivity analysis, and the ability to do repeated traditional simulation question "what if" analyses quickly. Rapid reporting of the response impacts the efficiency, effectiveness and satisfaction of human interactive design using repeated what if analyses.

The objective of this work is to apply a metamodel-based simulation optimization approach for solving the LSP in MTO supply chain. For this purpose, a DES model was firstly implemented as a tool in estimating Order Mean Flow Time (OMFT) performance. Secondly, multi-objective optimisation is achieved by applying desirability optimization methodology.

3 THE ADOPTED APPROACH

A qualitative description or analysis of the simulation results does not provide a deep understanding of the SC behaviour and could lead to erroneous conclusions in the decision making process. We know that experiments are natural parts of the engineering and scientific process because they help us in understanding how systems and processes work. The validity of the decisions taken after an experiment strongly depends on how the experiment was conducted and how the results were analyzed. Optimization technique and decision making tool are strongly amplified if Design of Experiment (DOE) or response surface methodology is used for correctly setting parameters levels, number of simulation runs and replications and for evaluating analytical model to be used for supporting the decision process (Longo and Mirabelli, 2008). Many recent research articles have been written on metamodel-based simulation optimization approach such as in (Longo and Mirabelli, 2008), (Li et al. 2009) and (Yalcinkaya and Bayhan, 2009).

Metamodels are used economically to learn about how the performance measure would behave over various regions of input-factor space and thus to estimate how the response would change at a particular point with a slight change in input factors, or perhaps to find approximate optimal settings for the input factors. In the proposed approach, whose flowchart is depicted in Fig.1, simulation metamodels are employed to obtain an effective mechanism for simplifying the interpretation of results from a well-planned experiment by interpreting the responses as a function of controllable input factors.

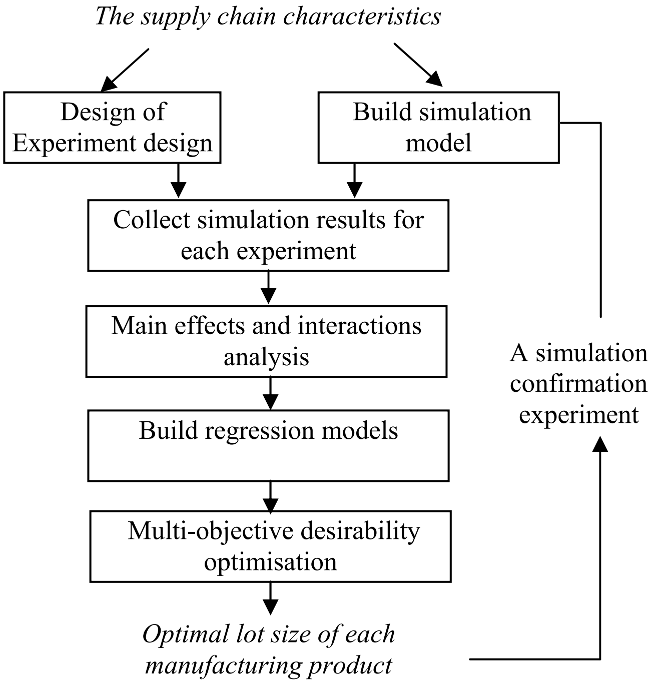


Figure 1: *Architecture of the adopted approach*

The adopted approach is carried out in three steps as indicated in Fig. 1. A Discrete Event Simulation (DES) model was firstly implemented as a tool in estimating (OMFT) performance. Secondly, Design of Experiment is applied to conduct simulation experiments. Finally, a multiple-objective optimization is achieved by applying desirability optimization methodology: the first one for experiments planning, the second one for understanding how input factors (lot-size) affect the SC performance and finally the third one for specifying the optimal factors configurations i.e. for giving the optimal lot-sizing of each manufacturing product.

3.1 Design of Experiments

The goal of performing a statically designed experiment is to obtain information as efficiently as possible. An experiment is a series of planned trials in which factors (independent variables) that are thought to affect the outcome are varied systematically and the outputs (dependant variables, also called responses) are measured and recorded. An experiment provides insight into how a SC behaves and, perhaps, why it behaves as it does. There are principally two types for designing an experiment: full factorial design and fractional factorial design. The full factorial design has the advantages that all kinds of main effects and interactions can be considered. However, since all combinations are to be tested, the number of experiments increases exponentially (Montgomery, 2005).

An objective of DOE is to find an appropriate approximation for the true functional relationship between response and the set of independent variables. If the response is well modelled by a linear function of the independent variables, then the approximating function is the first order model. In the proposed approach, the relationship between the input (lot size of each manufacturing product) and output variables (i.e. SC performance measure) is assumed to be a first order model with two-factor interactions such indicated in Eq. (1). Let *Y* be one of the performance measures, let X_i be the factors (with x_i varying between the levels) and let β_{ij} be the coefficients of the model.

$$Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i<j}\sum \beta_{ij} X_i X_j + \varepsilon \qquad (1)$$

$$\varepsilon \rightarrow \mathrm{NID}(0,\sigma^2)$$

Where *n* denotes the number of factors and NID indicates that the deviations (the residuals) have independent (and identical) normal distributions.
Desirability appears to be first proposed as a criterion for response optimization by Harrington (1965) and popularized by Derringer and Suich (1980). The first step in defining a desirability function is to assign values to the responses that reflect their desirability. The Multi-objective desirability optimisation method involves transformation of each predicted response, *ŷ,* to a dimensionless partial desirability function, d_i, which includes the researcher's priorities and desires when building the optimization procedure. One or two-sided functions are used, depending on whether each of the n responses has to be maximized or minimized, or has an allotted target value. If the response i is to be maximized the quantity d_i is defined as (Montgomery, 2005):

$$\begin{cases} d_i = \left(\dfrac{\hat{y} - A}{B - A}\right)^{w_i} & \text{If} \quad A \le \hat{y} \le B \\ d_i = 1 & \text{If} \quad \hat{y} > B \\ d_i = 0 & \text{If} \quad \hat{y} < A \end{cases} \qquad (2)$$

Likewise, d_i can be defined when the response is to be minimized or if there is a target value for the response. In Eq. (2), *A* and *B* are, respectively, the lowest and the highest values obtained for the response i, and w_i is the weight. d_i ranges between 0, for a completely undesired response, and 1, for a fully desired response. In both cases, d_i will vary non-linearly while approaching the desired value. But with a weight of 1, d_i varies linearly. In this work, we chose weights equal to 1 for all responses. The partial desirability functions are then combined into a single composite response, the so-called global desirability function *D*, defined as the geometric means of the different d_i values as indicated in Eq. (3).

$$D = \left(\prod_{i=1}^{n} d_i^{p_i}\right)^{\frac{1}{n}} \qquad (3)$$

A value of *D* different from zero implies that all responses are in a desirable range simultaneously and, consequently, for a value of *D* close to 1, the combination of the different criteria is globally optimum, so the response values are near the target values. In Eq. (3), p_i is the relative importance assigned to the response i. The relative importance pi is a comparative scale for weighting each of the resulting d_i in the overall desirability product and it varies from the least important ($p_i = 1$) to the most important ($p_i = 5$). It is noteworthy that the outcome of the overall desirability *D* depends on the pi value that offers users flexibility in the definition of desirability functions. In this work, we have chosen relative importance equal to 1 for all responses. Note that the use of desirability requires the designation of performance targets. In addition, maximizing desirability is a multi-objective optimization problem.

After the overall desirability function was defined, input variables to maximize the overall desirability function by the optimizing algorithm are determined. In this work, response optimizer tool of the Minitab software package is used for finding global optimum points. The search of the maximum desirability function is iterative which is based on reduced gradient search algorithm with multiple starting points. Detailed description of this local search algorithm can be found in (Bazaraa et al. 2006).

4 SUPPLY CHAIN DESCRIPTION

The SC configuration investigated in this research is shown in Fig. 2. Firstly, (Enns and Suwanruji, 2005) provide the same case study in MTS sector. Their problem has been revised and considerably modified to take into consideration MTO environment.

A detailed process description of the SC is a mandatory step for understanding what is implemented inside how the simulation model works. The SC under study is composed of six locations (entities). Two locations, L1 and L2, serve a distribution or retail function and are exposed to independent customer order. Locations L3, L4, L5 and L6 serve a production function. These locations may be considered to be capacity constrained because time delay operations are assumed. The SC under study belongs to multi-stage category. Each finished product (P1, P2 and P3) has component items (manufacturing products) as indicated by the Bill-of-Distribution (BOD) and the Bill-of-Material (BOM). Fig. 3 describes BOD and BOM dictating the flow of material. Note that the BOM also shows the quantity of items required by each finished part. The number in brackets beside the part number shows the requirements for all finished part order.

Part types P1 and P2 are both derived from P4. P3 is derived from P7. Since P7 is also a component of P4, the parts going directly to L2 could be considered spare or repair parts. At L3, P4 is assembled from three unit of P5, one unit of P7 and one P8 parts. At L5, P7 is produced from two units of P6. At L4, P8 is produced from one unit P6 and P5 is produced from one unit of raw material RM5. At L6, P6 is produced from one unit of raw material RM6. Supplies of RM5 and RM6 are assumed to be unlimited.

4.1 Model assumption

We consider a situation in which several types of parts are produced on the same SC. If the production is changed from one type to another, a set-up is needed. For some reasons, such as a large assortment of parts which is subject to regular changes, a highly uncertain demand, or unique parts, no safety stocks can be kept and we have to produce according to customer's specifications.

For specificity, this research makes the following assumptions concerning the simulation parameters. For all part types, it was assumed that the required lot-size order quantity was not available from the upstream supplier before shipments could be released (i.e. lot splitting is allowed).

Furthermore, for assembly operations, it was assumed that the required lot-size quantities of all components were also not available before any components were released for shipment. A common transit time was then applied to all components. So, arrival at the assembly location was simultaneous. The transit times are shown along side the arrows in Fig. 2. Moreover, when there are capacities constraints, lots arriving at manufacturing locations must undergo a setup time and a lot processing time. Mean setup and part processing times for processed and assembled parts are displayed in Table 1.

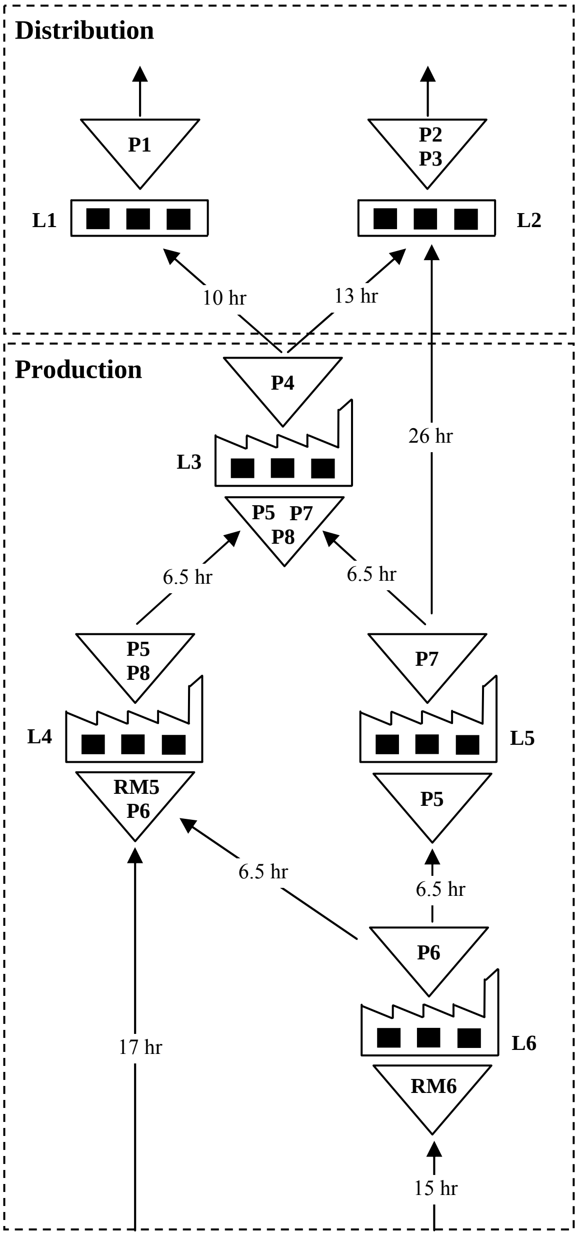
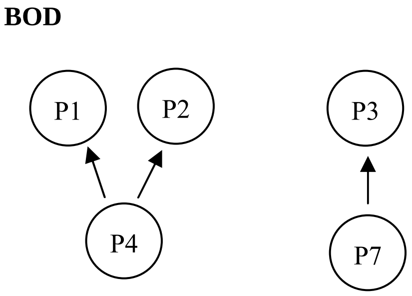


Figure 2: *Configuration of the supply chain network*



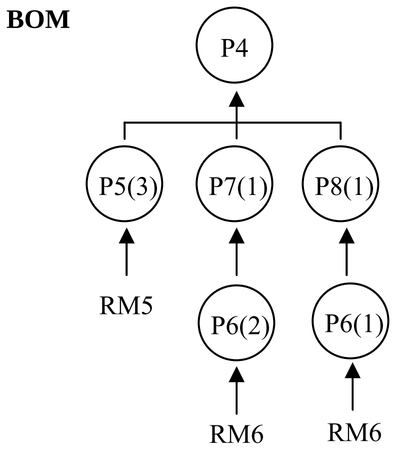


Figure 3: *Bills of Distribution and Materials*

The lot setup times are stochastic and follow a normal distribution with a coefficient of variation of 0.3. The lot processing times are deterministic and based on multiplying the lot size and times the fixed part processing time. Processing of all lots in queue is based on FCFS (First-come, first-served). Transit times, also shown in Table 1, are defined as the time to move an available lot of inventory from an upstream location to a downstream location. The transit times for all part types were assumed to be stochastic and follow a gamma distribution with a coefficient of variation of 0.1. No capacity constraints were assumed for inventory transportation.

Part type	Mean Setup time (hr)	Part Processing time (hr)	Mean Transit Time (hr)	Lot size
P1	0.5	0.009	10.0	200
P2	0.5	0.011	13.0	200
P3	0.9	0.023	26.0	300
P4	1.2	0.014	6.5	unknowns to be optimized
P5	0.24	0.002	17.0	
P6	0.50	0.003	15.0	
P7	0.8	0.006	6.5	
P8	1.6	0.007	6.5	

Table 1: *Supply chain data*

Furthermore, customer order which consists of fixed lot size of same product type follows a gamma distribution with a mean of 4000 units per week. One week is assumed to be equal to five working days. Time is given in hours, using the assumption there are 40 hours per week (or 8 hours per day. Daily order variation is determined by the basis of having a week order coefficient of variation of 0.1. Based on customer requirements and specifications, lot sizes for product types P1, P2 and P3 are compulsory fixed at 200 units, 200 units, and 300 units, respectively.

4.2 Performance measures

Many performance measures (metrics) can be considered for SC analysis such as work-in-process, mean tardiness, mean flow time and others. The main is thing, the coherence between the criteria of performance which guarantees the overall performance of the SC. In MTO production strategy, the main priority is to minimize mean lot tardiness in order to avoid associated penalties. On the other hand, it is also important to minimize mean lot earliness and its related extra storage costs. For this reason, the most appropriate performance measure would be the OMFT. There is a fixed target value (delivery promise date) proposed for each customer order. This target value must be framed between the lower and the upper values which are fixed to reduce cost as indicated in Table 2.

Performance measure	Lower (hr)	Target (hr)	Upper (hr)
OMFT P1	57	60	63
OMFT P2	62	65	68
OMFT P3	57	60	63

Table 2: *Order supply chain targets*

5 SIMULATION RESULTS AND OPTIMIZATION

The simulation model is developed using Arena 10.0 provided by Rockwell Software (Law and Kelton, 2000). The main portion of the model's operation will consist of logic modules to represent order arrivals, SC locations, and order delivery. For instance, the module "*Create P1 order*" ensures the entry of the product P1 lots within the system. Then each lot is assigned a set of attributes such as part type and sequence routing, via the module "*Assign P1 attributes*" Additionally, as the part proceeds through the SC, different attributes record the time delays associated with material handling, setup and processing time. All locations can be modeled by a set of machines, which each one is modeled using the "*Enter-Process-Leave*" module sequence. Finally, each order leaves the SC through the module "*Dispose*".

Once a simulation model of SC system has been built and verified, we can use it to analyse the SC performance according to factorial experimental design.

5.1 Design of Experiments

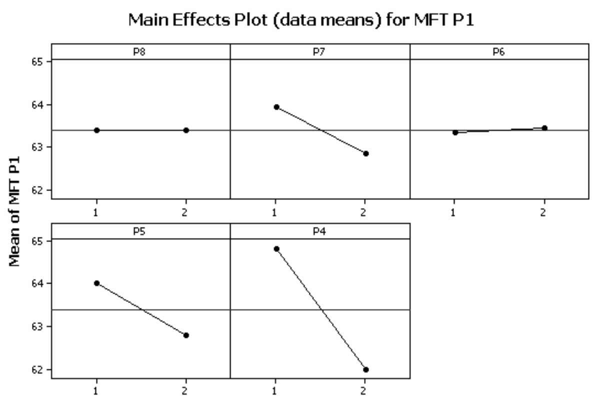
Before using DOE notation to divide the parameters into several levels, it is necessary to assign the variables for the operational parameters. In this study, we have chosen, for each manufacturing part, two levels: level 1 consists in a lot size of 100 units and level 2 consists in a lot size 500.

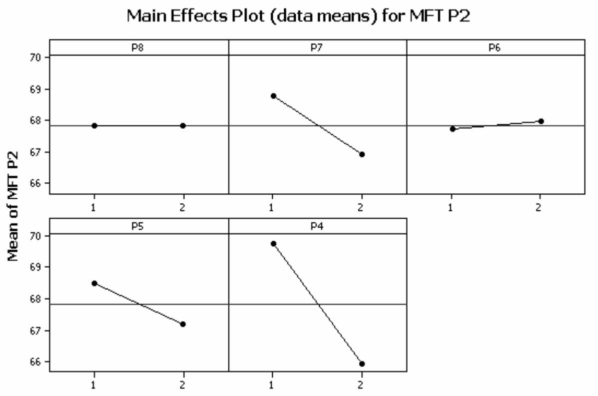
Several simulation runs were made for each SC configuration, each run length is fixed at 550 000 hours. The results of these simulation runs that are realized with the help of the simulator Arena 10 were averaged. The result of these runs is shown in Table 3.

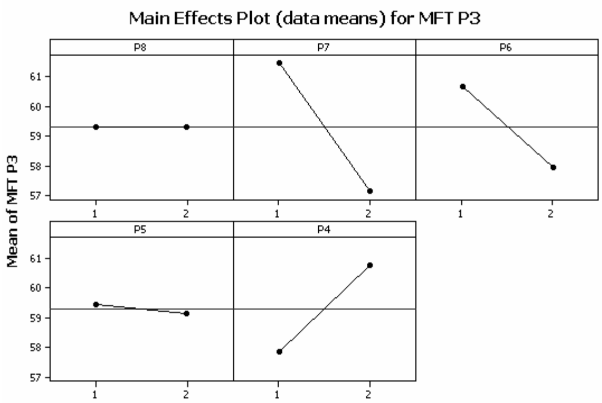
Exp.	Manufacturing part lot levels					MFT for each Finished parts (hr)		
	P4	**P5**	**P6**	**P7**	**P8**	**P1**	**P2**	**P3**
1	1	1	1	1	1	65.38	72.08	61.19
2	1	1	1	1	2	65.38	72.08	61.18
3	1	1	1	2	1	63.20	68.55	56.65
4	1	1	1	2	2	63.21	68.56	56.65
5	1	1	2	1	1	67.62	72.15	59.14
6	1	1	2	1	2	67.62	72.14	59.14
7	1	1	2	2	1	64.15	69.26	54.12
8	1	1	2	2	2	64.15	69.26	54.12
9	1	2	1	1	1	65.93	69.74	62.08
10	1	2	1	1	2	65.93	69.74	62.08
11	1	2	1	2	1	64.37	67.80	55.87
12	1	2	1	2	2	64.37	67.80	55.88
13	1	2	2	1	1	64.78	69.70	59.65
14	1	2	2	1	2	64.78	69.70	59.65
15	1	2	2	2	1	63.11	68.87	53.96
16	1	2	2	2	2	63.12	68.87	53.96
17	2	1	1	1	1	63.15	68.34	63.61
18	2	1	1	1	2	63.16	68.34	63.61
19	2	1	1	2	1	63.64	64.73	61.14
20	2	1	1	2	2	63.63	64.72	61.14
21	2	1	2	1	1	62.06	67.09	60.78
22	2	1	2	1	2	62.06	67.09	60.78
23	2	1	2	2	1	62.90	65.72	58.91
24	2	1	2	2	2	62.91	65.73	58.90
25	2	2	1	1	1	61.22	65.36	63.71
26	2	2	1	1	2	61.21	65.36	63.71
27	2	2	1	2	1	59.90	65.14	61.14
28	2	2	1	2	2	59.90	65.15	61.14
29	2	2	2	1	1	61.43	65.62	61.60
30	2	2	2	1	2	61.42	65.61	61.59
31	2	2	2	2	1	61.50	65.24	55.19
32	2	2	2	2	2	61.51	65.24	55.20

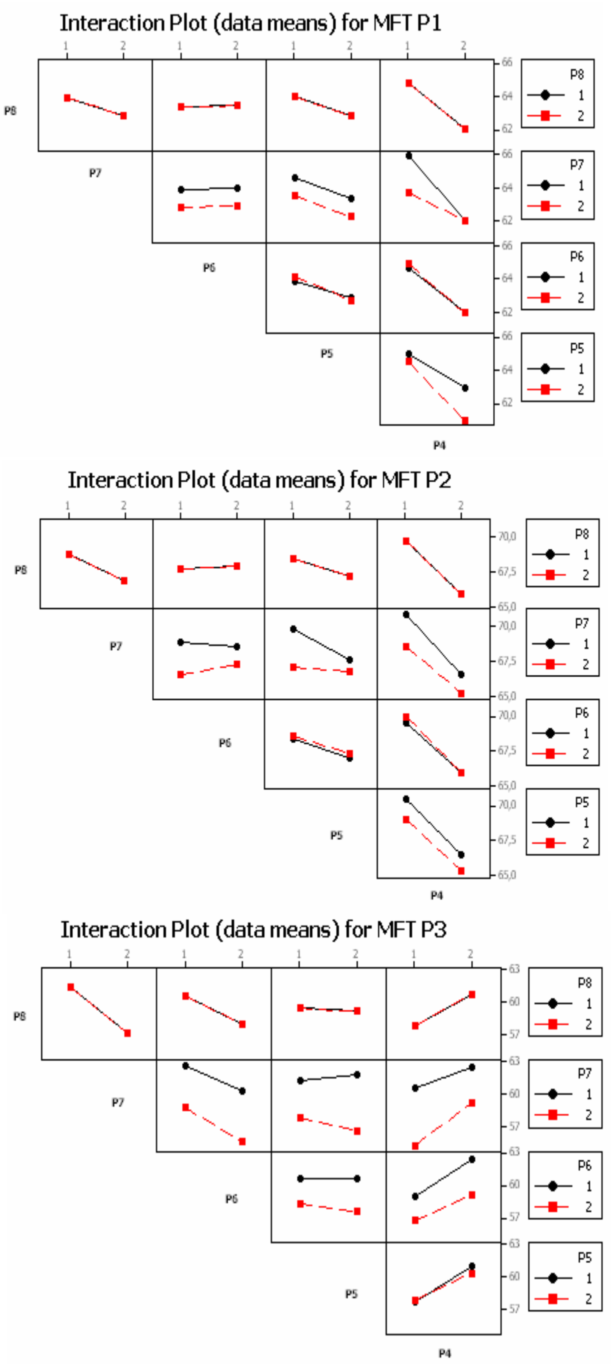
Table 3: *The 2^5 factorial design configurations*

Based on the output of the simulation experiments, further analysis is conducted for the fundamental understanding of SC. Due to multiple decision variables involved, main effects plots and second-order interaction effects plots are obtained using Minitab 14 software to demonstrate the magnitudes of each factor. The result is shown in Fig. 4. The points in the plot represent the mean of OMFT at the various levels of each decision variable.








Interaction Plot (data means) for MFT P1

Interaction Plot (data means) for MFT P2

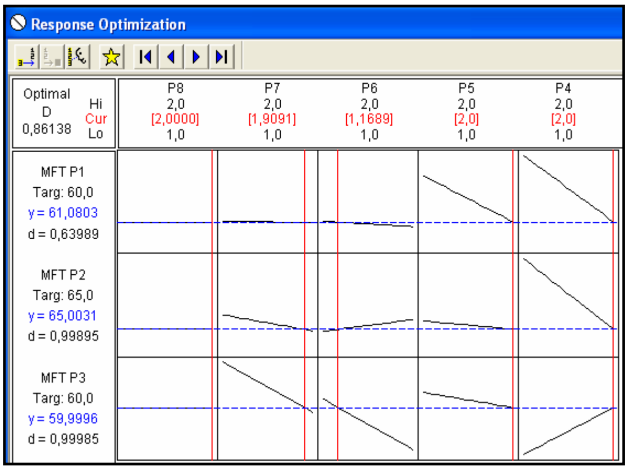
Interaction Plot (data means) for MFT P3

Figure 4: *Main effect plots and interaction plots for OMFT for each finished product*

5.2 Multi objective optimization

After planning the experiments and identifying the most important factors of the model, these factors are used as input data for multi-objective desirability optimization. This optimization tool is integrated in many software packages such as Minitab, Statistica, JMP software etc.

Applying Eq. (2) for each response measure, we obtain in optimal configuration that the individual desirability for MFT P1 is 0.639; the individual desirability for MFT P2 is 0.998 and the individual desirability for MFT P3 is 0.999. The response optimization consists in determining how the solution has satisfied the combined goals for all the responses. Composite desirability has a range of zero to one. One represents the ideal case; zero indicates that one or more responses are outside their acceptable limits. Composite desirability is the weighted geometric mean of the individual desirability for the responses as presented in Eq. (3). The composite desirability for all these three variables is 0.861. To obtain this desirability, we would set the factor levels at the values shown under global solution in the Fig. 5. That is, Lot size of each product P4, P5 and P8 would be set at 500 units, Lot size of P6 would be set at 168 units and Lot size of P7 would be set at 464 units.


Response Optimization

Optimal D 0,86138		P8	P7	P6	P5	P4
	Hi	2,0	2,0	2,0	2,0	2,0
	Cur	[2,0000]	[1,9091]	[1,1689]	[2,0]	[2,0]
	Lo	1,0	1,0	1,0	1,0	1,0

MFT P1
Targ: 60,0
y = 61,0803
d = 0,63989

MFT P2
Targ: 65,0
y = 65,0031
d = 0,99895

MFT P3
Targ: 60,0
y = 59,9996
d = 0,99985

Figure 5: *Multi-objective optimization based on desirability functions*

Since the optimum levels of input factors were determined using regression models, confirmatory simulation experiment was needed at optimum input levels (optimal lot size for each manufacturing product). In the one hand, output variables predicted using response optimisation (Fig. 5) are 61.08 hr for OMFT P1, 65.00 hr for OMFT P2 and 59.99 hr for OMFT P3. On the other hand, the output variables measured using the simulation confirmation experiments in the optimal conditions are 60.96 for OMFT P1, 64.90 OMFT P2 and 59.62 for OMFT P3. As can be seen, the predicted output values are close to the measured output values for all OMFT values. Therefore, we conclude that the optimisation approach is quite adequate for using as a decision support tool.

6 CONCLUSION & FUTURE RESEARCH

This research proposed a new approach for the lot-sizing problem in MTO supply chain. The proposed approach is based on combining discrete event simulation, factorial design, and multi objective desirability optimisation. The supply chain under study which operates in MTO environment (no possibility for stock keeping and limited production capacity) is characterized by multi-product, multi-stage, multi-location production planning with capacity-constrained and stochastic parameters such as lot arrivals order, transit time, setup time, processing time etc.

To the best of our knowledge, this is the first paper in which a metamodel-based simulation optimization approach is used to solve a lot sizing problem. The adopted approach is a logical and methodical approach which makes it easily portable into practice. For that reason, designs of experiment and desirability optimization tool are available in many commercial software packages including Minitab, Statistica and others.

It should be noted that the motivating case study is just a notional example. Our perspective should give more extensive testing on different problems to support the adopted approach application in supply chain management. Details and others real benefits of the application of the metamodel-based simulation optimization approach into real-life case study will be presented at our subsequent publications.

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