

A MULTI-LEVEL LOT SIZING PROBLEM APPLICATION

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ABSTRACT

This research presented a multi-level lot sizing problem application with an extensive model to solve a problem with a real demand forecasted from a sales record. The model here is defined as multi-item multi-level multi-period capacitated lot sizing by using Genetic algorithm. The first experiment is focused on finding the best solution found in the model compared to the initial feasible solution by using different crossover rates and mutation rates. The second experiment is an extension to the solution found in the first experiment, by conducting four case studies, each with a different cost reduction. Therefore, it is aimed to find the effect of each cost on the solution and provide a recommendation to the manufacturer on the cost effect. For the forecasting model, all products have a decreasing trend both in the sales records and in the forecasted data. For the lot sizing model, the best solution for the model is obtained by Genetic Algorithm run with the crossover rate of 0.2 and the mutation rate of 0.1. The best solution has a 21.03% reduction in terms of total cost compared to the initial feasible solution. The case studies result showed the most significant change is made in case III (10% over-capacity production cost reduction), which reduces the total cost by 6.90% while in other cases have very small significant changes.

Keywords: A Multi-Level Lot Sizing, Multi-Period, Application, Genetic Algorithm, Forecasting

INTRODUCTION

In the past few decades, the concern in the economics has been increasing significantly, which promotes the importance of lot-sizing problem which has been growing continuously in area of science management. The lot-sizing problem is very much related to the logistics and supply chain field including transportation and inventory management. The simplest and the first model for lot-sizing technique is dynamic lot-size algorithm developed by Wagner & within (1958), which is a generalization of the Economic Order Quantity (EOQ) model. One of the challenges in the lot-sizing model is the Multi-Level Lot-Sizing (MLLS) with extended parameters, which is a lot-sizing in consideration of the parent-child item relationship (Stadtler, 2011). This problem deals with determining the production lot-sizes of several items, each of which has a particular period, to minimize costs including setup cost, inventory holding cost, backlog cost, and over-capacity (Sum, Png & Yang, 1993; Davooi & Rezaei, 2011; Almada-Lobo et al., 2015). MLLS enables cost-saving in various areas, particularly in logistics and supply chain. Due to its practical significance, it is widely researched in supply chain management and can be utilized in numerous industries (Gansterer, Födermayr & Hartl, 2021).

In a manufacturing production system, end items are usually made up with several intermediate products which, in turn, consist in combinations of components (purchased parts and raw materials). Each end item is therefore described by a bill of materials, which is the product recipe. When considering the issue of satisfying the demand for end items emanating from customers, the right quantity of each sub-component must be made available at the right time and if possible, at the lowest cost. As products are associated with holding and set-up costs, different inventory policies lead to different costs and determining an optimal policy is a core concern (Pochet & Wolsey, 2006). The MLLS problem is to find a sequence of lot sizes that minimizes the sum of set-up and inventory carrying costs, while meeting the demand for end items over a T-period planning horizon. The objective function in general for a MLLS problem usually consists of the sum of purchase or production costs, set-up and inventory holding costs for all items over the 2-planning horizon (Melega, de Araujo & Jans, 2018). Note that the possibility of time-varying unit purchase and production costs, inventory costs and set-up costs is allowed. There are mainly three constraint equations for the problem: first, the flow conservation constraint for item. It defines the inventory level for the item at the end of period. The second constraint is the gross requirements which consist of the external demand when end items are considered, and result from the lot sizes of immediate successors for component items. Finally, the third constraint guarantees that a set-up cost will be incurred when a batch is purchased or produced.

The main objective of the research is to forecast the future demand of the products and plan the amount of raw material producing in each period to minimize the total cost, which consists of setup cost, holding cost, backlog cost, and overtime cost. First, raw demand data will be used to forecast demand in periods ahead. After the demand is settled, the problem will be solved by creating a mathematical model and implementing the model into the software. As this research was conducted with four case studies in Thailand, the results can be utilized and applied to other businesses and industries in Thailand. This is particularly important and will help Thailand develop its logistics and supply chain management. This is in line with Thailand's 12th National Economic and Social Development Plan in which Strategy 4.7 focuses on logistics and supply chain management development which in turn encourages trade promotion and facilitation (NESDB, 2017).

The paper is organized with a literature review on forecasting method, forecasting technique, and lot-sizing model which are discussed after the introduction section. Next, research methodology is described to illustrate mathematical models used in solving forecasting and optimization problems. The results are then obtained from the four case studies are presented indicating total cost reduction. Finally, the conclusion and recommendations are discussed in the last section of the paper.

LITERATURE REVIEW

Forecasting Method

Forecasting is the process of making predictions of the future based on past and present data and analysis of trends. A commonplace example might be estimation of some variable of interest at some specified future date. Prediction is a similar, but more general term. Both might refer to formal statistical methods employing time series, cross-sectional or longitudinal data, or alternatively to less formal judgmental methods. Usage can differ between areas of application. Risk and uncertainty are central to forecasting and prediction; it is generally considered as a good practice to indicate the degree of uncertainty attaching to forecasts. In any case, the data must be up to date for the forecast to be as accurate as possible (Armstrong, 2001).

Forecasting method can be generally categorized into two groups: qualitative and quantitative. Qualitative forecasting techniques are subjective, based on the opinion and judgment of consumers, experts; they are appropriate when past data are not available. They are usually applied to intermediate- or long-range decisions. For quantitative forecasting models are used to forecast future data as a function of past data. They are appropriate to use when past numerical data is available and when it is reasonable to assume that some of the patterns in the data are expected to continue into the future (Wheelwright, Makridakis & Hyndman, 1998). These methods are usually applied to short- or intermediate-range decisions (Mori, Mendiburu, Álvarez & Lozano, 2015). Therefore, this research utilizes quantitative techniques to obtain the visual information of the future demand. These techniques are based on models of mathematics and in nature are mostly objective. As the MLLS problem deals with time-based data, time-series method is selected to obtain the demand forecast (Mou, Ji & Tian, 2018).

Forecasting Techniques

The simplest way to smooth a time series is to calculate a simple, or unweighted, moving average (Khosravi, 2015; Li, Bissyandé, Klein & Traon, 2016). This is known as using a rectangular or 'boxcar' window function. A major drawback with the simple moving average is that it lets through a significant amount of the signal shorter than the window length. Worse, it actually inverts it. This can lead to unexpected artefacts, such as peaks in the smoothed result appearing where there were troughs in the data. It also leads to the result being less smooth than expected since some of the higher frequencies are not properly removed. A slightly more intricate method for smoothing a raw time series (NIST/SEMATECH, n.d.) is to calculate a weighted moving average (Field, 2020). The next forecast technique is Exponential smoothing which was first suggested in the statistical literature without citation to previous work by Brown (1956), and then expanded by Holt (1957). Exponential smoothing can be categorized into 2 methods: simple and double. Simple exponential smoothing does not do well when there is a trend in the data, which is inconvenient (Sidqi & Sumitra, 2019).

Lot-Sizing Model

Economic Lot Size (ELS) was first developed and introduced around 1913. It balances the inventory cost against the setup cost over a range of batch quantities (Strategos-International, n.d.). In this principle, the ELS is where its total cost is minimized. The ELS cannot be efficiently used as stated by some supporters of 'Lean Manufacturing' and 'Theory of Constraints'. It was argued that the operation should produce the needs of downstream customer immediately in batches of one unit. The number illustrates a representative ELS model. The model carries out the calculation of the overall production cost per unit over a range of batches. The batch quantity which has the smallest unit cost is the ideal one for the ELS. The model categorizes overall total cost into three types of cost: Direct Cost, Setup Cost, and Holding Cost (Storage Cost). This accelerates the calculation and aids comprehension (Pyrzcz & Deutsch, 2014).

Dynamic lot-size model was introduced Wagner & Whitin (1958). The dynamic lot-size model in the inventory theory is a generalization of the Economic Order Quantity (EOQ) model in which demand for the product varies over time. In many practical situations, the demand is known precisely for a certain number of periods (Sanni, Jovanoski & Sidhu, 2020). Such situation frequently becomes apparent in material management, which is where the item is a raw material or a component part or an assembled part in a manufacturing process. Demand for the item for several predicted periods can be assumed from the master production schedule during the Material Requirements Planning (MRP) process.

All approaches reviewed so far are for the single level case only. In most real-world situations, however, the complex multi-level item assembly structures are faced. Thus, solution procedures capable of dealing with these problems are needed. Consequently, multi-level lot sizing has attracted many scholars to conduct research in this particular problem. Many scholars have considered a multi-level WW type of problem (Maiti, Mandal & Pramanik, 2019) in which the capacity constraints are ignored. Most of them have tested the so-called ‘improved heuristics’ where methods for the single-level WW problem are applied level by level to construct a feasible plan. Complexity results for incapacitated, multi-level lot sizing is done by many scholars (Gansterer, Födermayr & Hartl, 2021; Toledo, Silva, Hossomi, França & Akartunalı, 2015; Karimi-Nasab & Seyedhoseini, 2013). The literature on multi-level lot sizing and scheduling is sparse. The only work where multi-level lot sizing and scheduling is done simultaneously under quite general assumptions such as general item assembly structures and multiple machines is documented by Copil, Wörbelauer, Meyr & Tempelmeier (2017). Research on several variants of the multi-level PLSP is also summarized by Wei, Amorim, Guimarães & Almada-Lobo (2019). It can be proven that the (multi-level) DLSP and the (multi-level) CSLP are special cases of the (multi-level) PLSP.

Problem Definition

In a manufacturing production system, end items are usually made up with several intermediate products which, in turn, consist in combinations of components (purchased parts and raw materials). Each end item is therefore described by a bill of materials, which is the product recipe. When considering the issue of satisfying the demand for end items emanating from customers, the right quantity of each sub-component must be made available at the right time and if possible, at the lowest cost. As products are associated with holding and set-up costs, different inventory policies lead to different costs and determining an optimal policy is a core concern.

In this research, the data is processed through a forecasting technique before it can be used to determine the lot size of any period. The vital data to be applied to the problem is the sales record for the past two years, which will be used for T-period forecasting. There are seven types of products which have the sales record, and each product is described by bill of materials (a template of the Bill of Materials (BOM) in the problem is shown in figure 1). It defines the problem as multi-item multi-level multi-period capacitated lot sizing with backlog.

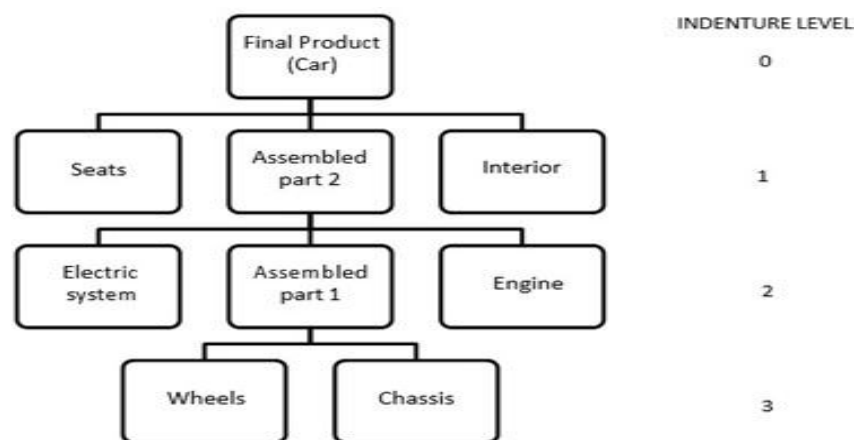


FIGURE 1
BILL OF MATERIALS (BOM) TEMPLATE USED IN THE PROJECT

In addition, the key assumption of this research is identified. Lead time for the raw material is varying, but the average lead time is calculated to be 1 month. A general multi-level product structure with several end products is considered.

RESEARCH METHODOLOGY

There are two main mathematical models are used to solve the problem: forecast and optimization model. Forecasting method is used to forecast the demand of products, which is used to determine the number of materials produced in each period. Once the Forecasting formula is formed, the forecasting problem is solved. After that, optimization model is formulated as the objective function for minimizing the total cost, which consists of setup cost, holding cost, over-capacity production cost, and backlog cost, restricted by a set of constraints. By solving the problem, the optimization software is used to obtain the solutions. After the results are carried out by various computational factors of Genetic Algorithm (GA), which are mutation rate and crossover rate, they will be collected and analyzed for the conclusion of the research. The research's aim is to determine production quantities of the materials and end-of-period inventory levels for the product in the period, as well as a setup pattern that minimizes the sum of setup, holding, backlog, and over-capacity production costs.

Data Collection

This research conducted based on real data of sales record and costs (holding cost, setup cost, backlog cost, and over-capacity production cost) of the companies in Thailand. Note that the cost used in this research is the average cost over the periods; however, the cost is varied is reality.

Mathematical Formulation

The forecasting mathematical model is applied regarding to the methods and formulas in the literature to determine level of the item in every product for given period ahead. The raw data sequence of observations is represented by y_t , beginning at time $t=1, 2, \dots, T$. We use \hat{y}_t to represent the smoothed value for time t , and \hat{y}_t is our best estimate of the trend at time t . The output of the algorithm is now written as \hat{y}_t , an estimate of the value of F at time t based on the raw data up to time t . Double exponential smoothing is given by the formulas:

And for by

Where α is the data smoothing factor, β stand for the trend smoothing factor

Finally, the beta value with the least SSE is selected as the trend smoothing factor for each product. To forecast beyond T :

The objective function is the sum of setup, inventory holding, over-capacity production, and backlog costs for all items over the planning horizon. Note that the possibility of time-varying unit purchase and production costs, set-up costs, inventory costs, backlog costs, and over-capacity costs is allowed. There are mainly four constraint equations for this problem. The first constraint is the flow conservation constraint for item. It defines the inventory level for the item at the end of period.

The second constraint is the gross requirements which consist of the external demand when end items are considered, and result from the lot sizes of immediate successors for component items. The third constraint guarantees that a set-up cost will be incurred when a batch is purchased or produced. Finally, the fourth constraint is the backlog constraint, which defines the backlog level when the demand in a period is not satisfied.

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There are two mathematical models formed to solve the problem regarding to the data collected. The first model is the determine level of the item in every product for given period ahead. The forecasting method is used to forecast the demand for the next 24 periods of all seven products, based on 24-period sales records. After the demand for the next 24 periods is determined, the demand together with the lot sizing mathematical model will be applied and solved. After the level of the item in every product for given period ahead have been calculated, the second mathematical model, the optimization model is formed with principal objective function to solve the problem based on data available.

RESEARCH RESULTS

There are two experiments implemented in the project. The first experiment is conducted to seek the best solution from a particular mutation rate and crossover rate by using the various rates and choose two particular rates that provide the best solution from the lot sizing model. The second experiment is four case studies, which are implemented after the best solution from the first experiment is obtained. The case studies are conducted by using a cost reduction scenario, 10% setup cost reduction in case I, 10% inventory holding cost reduction in case II, 10% over-capacity cost reduction in case III, and 20% backlog cost reduction in case IV.

The model is solved by GA from the initial solution created by using various crossover rate and mutation rate. The mutation rate is selected randomly and fixed at 0.1 and 0.2 to seek the best solution obtained by various crossover rates from 0.1-0.9 and 0.05-0.15. The mutation rate fixed at 0.1, the experiment conducted with various crossover rates shows that at the mutation rate of 0.1, the best solution from the optimization model can be obtained by the crossover rate of 0.2. The model run with the crossover rate of 0.2 and the mutation rate of 0.1 reduce the objective value (total cost) from the initial feasible solution by 21.03%. The result concludes that the solution obtained by mutation rate of 0.1 and the crossover rate of 0.2 provides the best solution for the optimization model. After that continuing from the experiment I. The result showed that the solution quality from various crossover and mutation rates has no significant difference. The crossover rate and mutation rate given improves the solution from 29359987 obtained from the initial solution to 23184683, which is improved by 21.03% in terms of total cost.

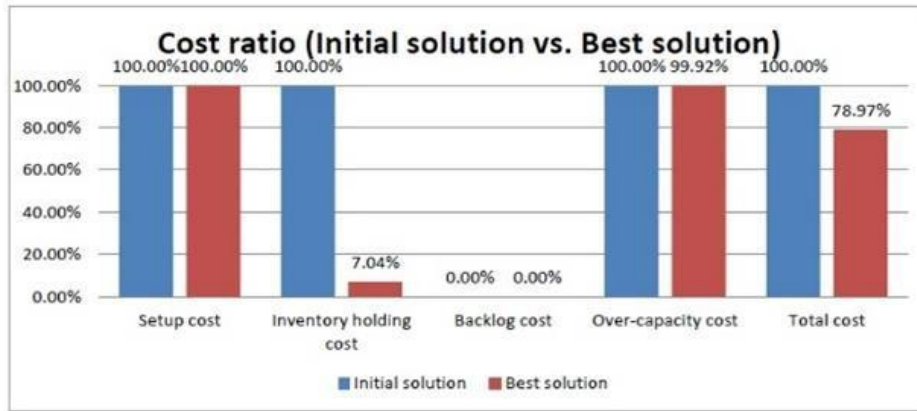


FIGURE 2
COST RATIO OF THE BEST SOLUTION COMPARED TO THE INITIAL FEASIBLE SOLUTION

Figure 2 shows that there is no change in setup cost and backlog cost from the two solutions, while there is a very slight reduction in over-capacity cost from the initial feasible solution to the best solution (0.08%). The major difference of the total cost between the two solutions comes from the inventory holding cost, which is reduced by 92.96% from the initial feasible solution.

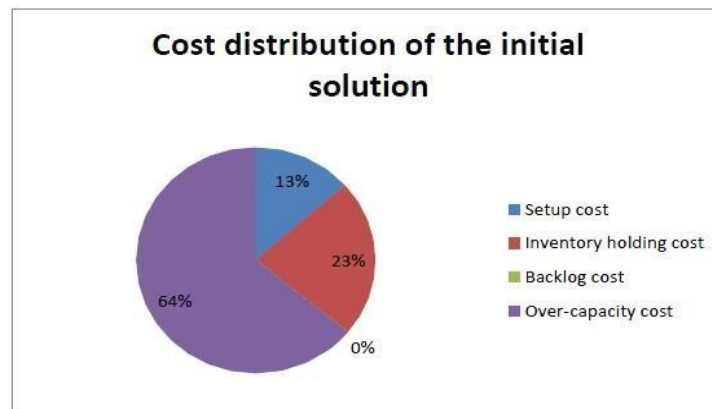


FIGURE 3
COST DISTRIBUTION OF THE INITIAL FEASIBLE SOLUTION

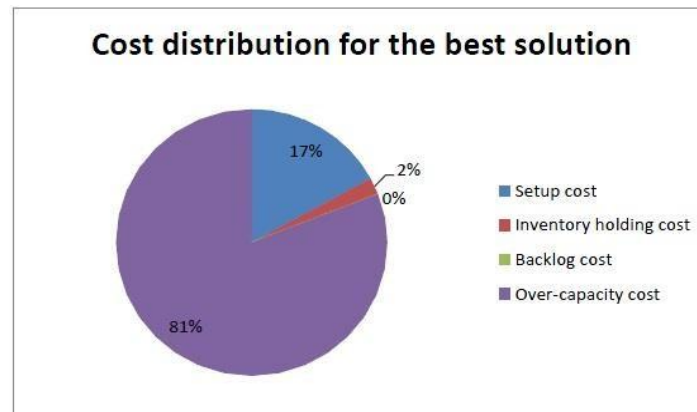


FIGURE 4
COST DISTRIBUTION OF THE BEST SOLUTION

Figures 3 and 4 show the cost distribution from the initial feasible solution and the best solution respectively. These figures show that most reduced cost portion in the solution is the inventory holding cost (21% in the initial feasible solution and 2% in the best solution.) most portion of the cost occurs in the solution is the over-capacity cost (62% for initial feasible solution and 82% in the best solution), while the setup cost portion changes from 11% in the initial feasible solution to 16% in the best solution. Two costs which are increasing regarding to the cost portion are due to relatively constant in these two costs while the total cost is reduced.

In case I, the setup cost is reduced by 10%, while the other three costs remain the same. There are two significant changes in the cost categories, which are 10% cost reduction in the setup cost and 56.37% cost increase in the inventory holding cost, with no significant changes in over-capacity cost (0.04% increase), and no change at all in backlog cost. There is no significant change in total cost from case I with the total cost reduction of 0.55% and therefore, it is not recommended for the manufacturer to invest their money to improve the manufacturing system which reduces the setup cost. There is no significant change in total cost from case II with the total cost increase of 0.78%. Therefore, it is not recommended for the manufacturer to invest their money to improve the manufacturing system which reduces the inventory holding cost. In case III, while the other three costs remain the same, there are two significant changes in the cost categories, which are 57.93% cost increase in the inventory holding cost and 9.96% cost reduction in the over-capacity cost, with no significant change's setup cost (0.13% reduction), and no change at all in backlog cost. There is a significant change in total cost from case III compared to any other cases, with the total cost reduction of 6.92%. In case IV, the backlog cost is reduced by 21%, while the other three costs remain the same. The result shows that there is only one significant change in the cost categories, which is 58.09% cost increase in the inventory holding cost, with no significant changes over-capacity cost (0.07% increase), and no change at all in setup cost and backlog cost. There is no significant change in total cost from case IV with the total cost increase of 1.31%. Therefore, it is not recommended for the manufacturer to invest their money to improve the manufacturing system which reduces the backlog cost.

Experiments II, case study, which are four case studies with four scenarios are implemented by using the crossover rate of 0.2 and the mutation rate of 0.1 and study each scenario for effects in total cost. There is only one case which made a significant change to the solution, which is case III – 10% over-capacity cost reduction. The solution in this case improved the total cost by reducing it by 6.92% from the best solution obtained from the model, while in case I, II, and IV made no significant change to the solution 0.62% reduction, 0.88% increase, and 1.31% increase, respectively. In summary, case III has the best solution in terms of total cost compared to three other cases. The scenario gives a significant reduction in total cost by 6.92%. From this study, it can be concluded that, if the capital spending on reducing the over-capacity cost over 24 periods is less than £1599040, the improvement would be worth investing. However, in the realistic situation, further feasibility study must be conducted to see if the manufacturer should invest in improving the manufacturing system to reduce the over-capacity cost. There are also many factors which affect the feasibility other than the production management or inventory management such as economics, marketing, and political policy.

CONCLUSION

This research addresses the problem of demand forecasting, and multi-level lot sizing model with real-life parameters and constraints problem. The objective is to minimize the total cost, which consists of setup cost, inventory holding cost, backlog cost, and over-capacity cost. These two problems are treated separately in the mathematical models and solving methods. There are also two experiments conducted based on the lot sizing model, which are the study of genetic operators

(mutation rate and crossover rate) and four case studies of cost scenarios. To solve this problem, the research is conducted in two phases. The first phase is focused on finding a set of demands by using forecasting method. The second phase of the study is focused on lot sizing model, which is divided into two experiments. The first experiment is focused on finding the best solution found in the model compared to the initial feasible solution by using different crossover rates and mutation rates, a particular crossover rate and mutation rate which provide the best solution concludes the experiment. The second experiment is an extension to the solution found in the first experiment, by conducting four case studies, each with different cost reduction. The purpose is to find the effect of each cost on the solution and provide a recommendation to the manufacturer about the cost effect. For the forecasting model, all 7 products have a decreasing trend, both in the sales records and in the forecasted data. For example, the total forecasted product demand in period 1 is 22791 and the total forecasted product demand in period 24 is 17835, representing 21.75% reduction over 24 periods. The major reasons behind the decreasing sales are political policy, economy, and the same model produced over a time. There might be a spike in demand in the future when the manufacturer announces the new product model, which should be more interesting for problem as the model has to deal with the increasing demand which might change the decision variables in the problem.

For the lot sizing model, the best solution for the model is obtained by Genetic Algorithm run with the crossover rate of 0.2 and the mutation rate of 0.1. The best solution has a 21.03% reduction in terms of total cost compared to the initial feasible solution. For the case studies, the most significant change is made in case III (10% over-capacity production cost reduction), which reduces the total cost by 6.90%, while in other cases have very small significant changes. From this study, it can be concluded that, if the capital spending on reducing the over-capacity cost over 24 periods is less than £1599040, the improvement would be worth investing, subject to other real-life factors. The better solution might be achieved by giving more time with a more powerful computing tool through a bigger population size, as the model run with various genetic operators in this research usually find the first solution in 30000-50000 trials.

FUTURE RESEARCH

This research can be extended by improving current solution approach. It was discovered that in developing the solution, the software used to solve the problem is not efficient and it was time-consuming to find the solutions. The problem can be solved by implementing and applying other approaches to help searching for the solutions. In terms of improving solution quality, meta-heuristic approaches such as Genetic Algorithm (GA), Tabu Search (TS), and Simulated Annealing (SA) could be all applied to the lot sizing process (Kaku, Li & Xu, 2009; Kaku et al., 2014). Implementation of a more complex model such as an extension of this research should also be an interesting field of study. In demand set, stochastic demand model, seasonality, or randomness for the demand could be added to give more complexity to the problem. Also, internal and external factors which affect the decision variables or parameters might be added to give the complexity to the problem leading to a better application to the real-life situation. For the complexity of the problem, this research could be extended by involving the production control level. Production scheduling is a very interesting method to apply to the lot sizing model, rather than production capacity constraints used in this research. Machine availability and capacity must be also taken into consideration along with many other constraints constructed in the scheduling model. Another extension of the study which might interests people involving in business is to implement the model with the consideration of various business factors, such as marketing, financial feasibility,

operational feasibility, and business strategy. This extension can be used as a feasibility study for a certain type of industry or a case study in each industry.

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