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Optimization of Batch Volume in a Multi-Part Manufacturing System

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ABSTRACT : In this paper, the problem of finding the optimum batch sizes in a High mix, Low volume production line is addressed. Finding optimum batch sizes is a problem faced by many manufacturers in a High mix, Low volume production environment. However, increase in the variety of boards causes interruptions in the production process. Frequent setups can lead to small lots and low inventories. In contrast, bigger batch sizes save production time by having fewer setups but they increase inventory value. Lack of optimization causes more hindrances when there is a bigger product mix in a production environment. Finding optimum batch sizes is a problem faced by many manufacturers in a High mix, Low volume production environment.

Here, the problem of finding optimum batch sizes is solved using optimization techniques in Operations Research. Considering the nature of the research problem, a quantitative approach is adopted in this project. Furthermore, inspired by Setup Improvement theory, some improvements are suggested for the setup process.

The data required to solve the research problem was collected from company's ERP system. A proper optimization algorithm was developed using MATLAB algorithm programming. During building the optimization model and preparing the input data, it was decided that some of the boards should be excluded and not take part in the model. Barring such considerations, implementation of optimum batch sizing established to all the significant parts. The model which was iteratively and heuristically weaved utilized the approach of genetic algorithms. It was used not only for calculating the optimum batch sizes, but also to perform capacity analysis and investigating the effect of setup time reduction on both batch sizes and capacity.

The conclusions from the empirical part show that optimizing setup times can help producing smaller batch sizes. It also increases production capacity and system's flexibility. Operations Research methods also showed to be very effective tools that can lead to significant savings in terms of money and capital.

KEYWORDS: High mix-Low volume Production, Surface Mount Technology (SMT), Optimal Lot Sizing.

I. INTRODUCTION

Anyone involved in the practice of production planning and management of certain number of products is faced with two important questions that should be answered: when to produce and how much to produce? The advent of Enterprise Resource Planning (ERP) software like SAP (Systems Applications Products) or IFS (Industrial and Financial Systems) has made the answer to the first question very easy. However, the second question, how much to produce, still remains unanswered. The second question, famous as lot sizing problem, has an important role in plant's financial function. Inventories have long been seen as necessary evils. They are necessary since without them the customer service level of the plant falls down. They are evil because they tie up large amounts of capital to themselves and tend to decrease the plant's turnover rate. Finding an answer to this problem is quite complicated since there are many different variables involved in the process. Nonetheless, each manufacturing plant is unique, each production process is especial in its own way and they all involve different types of constraints and variables. Therefore, finding an answer that can be applied to all different situations is cumbersome.

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Although there are numerous articles addressing the issue of lot sizing in different production environments, there is a lack of research on using mathematical optimization tools with respect to addressing the problem in the context of electronic manufacturing systems. A typical example of such a system is a high mix, low volume production system which produces a high variety of products with low volumes trying to meet a highly variant and lumpy customer demand. Many assumptions that are the bases of the previous models do not apply in this context. Therefore, there is a need to investigate this problem separately.

II. RESEARCH PROPOSAL

A. Problem Formulation

Today there is a lack of knowledge and competence in companies regarding the use of mathematical optimization for finding optimum batch sizes. The smaller batch sizes will reduce the inventory and help the company toward production according to customer orders which is one of the aims of Lean manufacturing. However, increased number of long setups may decrease the available production time and expose the production line with the danger of unmet customer demand. Bigger batch sizes will reduce the number of setups and increase the available production time but they will also increase the inventory value. More products will be in stock for a longer period of time and they are exposed to deterioration. There will also be a need for a larger storage for keeping the items in stock. In addition, bigger batches are an obstacle for producing a high mix of products. Due to longer production time of bigger previous batches; each job should wait for a longer time until it can enter the line. The focus of this paper is to answer this question: What are the optimum batch sizes for a High mix, Low volume production line? In order to answer this question, two methods are used. Economic Order Quantities (EOQ) is the first method that is tested. Followed by that, the use of Operations Research (OR) techniques are investigated on lot sizing problem.

The aim is to explore the potential of utilizing mathematical optimization tools on a real case and to find a proper method to calculate the optimum batch sizes and to present the results.

B. Case Company

The case company chosen for this report is ATI Electronics Pvt. Ltd., an electronics manufacturing company. ATI Electronics was established in 1995.

Amongst different products of the company are the printed circuit boards (PCBs). Today, up to 188 different boards are produced in the company. High variety of boards and low volumes classify the production as High mix, Low volume. The need for frequent long changeovers forces the production line to produce the boards in batches. These boards are used as a component in company’s other final products or they are delivered directly to the customers as finished products. The boards are produced in one of the company’s production lines using Surface Mount Technology (SMT). The SMT assembly involves three basic processes: screen printing of the solder paste on the bare boards, automatic placement of components on the boards using two placement machines in series (one for small components and the other for large components), and solder reflow oven. There are inspections after the solder printing, placement machines and reflow oven. The boards are produced in batches. Batch sizes are specified in an ERP system called IFS. Whenever customer demand cannot be met by finished boards in inventory, a production order of a specified quantity is sent to the workstation through IFS.

C. Methodology and Data Collection

The nature of the batch sizing problem requires the description of the demand pattern, finding averages, dealing with large amount of numeric data and carrying on optimization procedures. Due to the nature of the research problem, it is necessary to continue with a quantitative approach.

The data required to solve the research problem was collected from company’s ERP system. This data includes information related to demand patterns for each board, prices, production quantities, cycle times, capacity and etc. The data from ERP system was in raw form and had to be processed before turning into meaningful information, therefore a great deal of time was spent on processing and manipulation of raw data using Excel. To continue, an optimization model was created using genetic algorithm which enabled this data to be used. This model was used for calculating the optimum batch sizes for different parts.

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III. ECONOMIC ORDER QUANTITY

A. EOQ Formula

Manufacturing companies face conflicting pressures to keep inventory level low enough to reduce inventory holding costs but at the same time high enough to avoid excess ordering or setup costs. A good starting point to balance out these two conflicting costs and to determine the best inventory level or production lot size is to find the economic order quantity (EOQ), which is a lot size that minimizes the sum of total annual inventory holding costs and setup. There are a set of assumptions that should be considered before calculating the EOQ:

1. The demand rate is constant and is known for certain.

2. No constraint is set for lot sizes (such as material handling limitations).

3. Inventory holding cost and setup cost are the only two relevant costs.

4. Decision for each item can be made independently from other items.

5. The lead time is constant and the ordered amount arrives at once rather gradually.

In order to calculate the EOQ, first we need to calculate the average quantity hold as inventory over the year. When all the five assumptions of EOQ are held, the cycle inventory for an item behaves as shown in Figure.

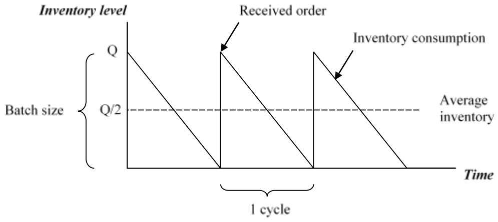

Fig 1: BATCH SIZES

The cycle begins by a batch size of Q held in inventory. As the time goes on, inventory is consumed at constant rate. Because the demand is constant and certain, the new lot can be ordered in time and be received precisely when inventory level falls into zero. Since inventory level varies uniformly between zero and Q, the average inventory level equals to half the lot size, Q/2.

$$Annual\ Holding\ Cost = (Average\ cycle\ inventory) \times (Unit\ holding\ cost) = \frac{Q}{2} \times H$$

And

$$Annual\ Setup\ Cost = (Number\ of\ setups\ per\ year) \times (Setup\ cost) = \frac{D}{Q} \times S$$

Where

C = total annual inventory cost

Q = lot size

H = cost of holding one unit in inventory for a year

D = annual demand in units

S = cost of setup for one lot

The number of setups per year is equal to annual demand divided by Q.

The total annual inventory cost which is depicted in Figure 11 is the sum of the two components of cost and is equal to:

$$Total\ cost = (Annual\ holding\ cost) + (Annual\ setup\ cost)$$

Or

$$Total\ Cost, C = \frac{Q}{2}(H) + \frac{D}{Q}(S)$$

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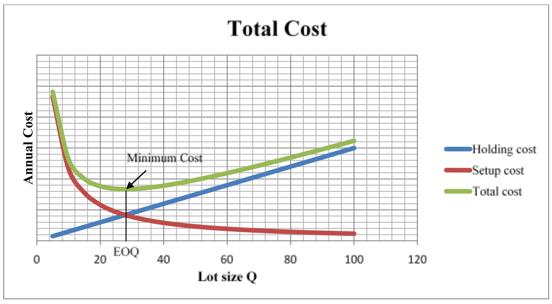

Fig 2: EOQ

The value of Q that minimizes the total annual cost is calculated by setting the first derivative of total cost formula with respect to Q, equal to zero (Hillier and Lieberman, 2001). Therefore:

$$First\ derivative = 0$$

$$\frac{dC}{dQ} = \frac{H}{2} - \frac{DS}{Q^2} = 0$$

$$Q^2 = \frac{2DS}{H}$$

$$Economic\ Order\ Quantity = Q = \sqrt{\frac{2DS}{H}}$$

B. Calculating EOQs

Through IFS system, we can find the current batch sizes used for different boards. In order to find the optimum batches for each board, the first idea was to calculate the EOQs for every board and compare them with the current batch sizes to get a general idea of the current situation. According to EOQ formula $\sqrt{\frac{2DS}{H}}$, there are three parameters that need to be identified for each board to calculate the economic order quantity: D, representing the annual demand for each board; S, representing the setup cost for each board and H, representing the annual inventory holding cost for each board. The annual demands for boards are obtainable through IFS.

The boards are represented by Xi in the table below. Minimum lot sizes are the current batch sizes used for production. They refer to the amount that should be produced if the demand cannot be met by the existing boards in inventory.

Some of the boards – which usually have low demand and high price – are produced only based on customer order quantity. Standard lot sizes are used to calculate the setup cost per each board. For example, if the standard lot size for a particular board is 30, the cost of setup for this type of board is divided over 30 to calculate the setup cost per board.

Table 1. Calculations of EOQs

Boards	Min Lot Size	Standard Lot Size	Annual Demand	Price	EOQ
X1	10	10	150	475.56	63
X2	20	30	24	338.64	30
X3	3	60	21	484.35	23
X4	10	10	62	737.79	32
X5	20	20	92	504.09	48
X6	20	20	328	247.47	129
X7	30	30	133	315.06	73
X8	30	40	690	187.92	214
X9	0	20	6	254.88	17
X10	3	3	24	1016.4	17

The logic behind economic quantities is to balance out the two costs of inventory holding and setups. The new economic quantities, as shown in the table above, are almost twice as big as the current batch sizes in most cases. As

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mentioned before, there is no doubt that the concept of economic lot sizes is entirely true. However, the value we choose as input data for the formula is our choice. The more accurate the data is, the more reasonable our answers will be.

If we assume that our defined setup cost is correct, then we should accept the results for these new batch sizes. In theory, if the setup cost is that high, then this conclusion is true. But the problem is that this definition of setup cost creates a problem in calculation of economic order quantities. If setup cost is the cost of lost production rather than salaries and overheads, then it is a variable quantity, not a fixed value. The number of setups can be increased without facing any cost as long as no production loss is created. The moment the capacity constraint is violated, a cost related to lost production is incurred. This cost increases linearly as production loss increases. The new defined setup cost can be assumed to have a pattern as illustrated in Figure:

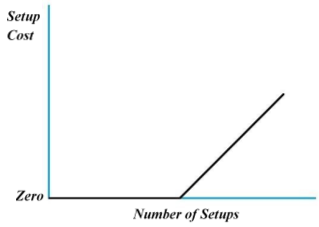


Fig 3: Setup Cost

The economic order quantity formula requires us to assume a fixed value for setup cost. By contrast, the new definition of setup cost as the cost of lost production assumes setup cost to be a variable. As it was mentioned before in the theoretic framework, setup cost is a consequence of the solution rather than a fixed parameter of the problem. Having setup cost as a variable makes it impossible to use EOQ formula for calculating optimal batch sizes and therefore the EOQ formula should be put aside. A new way should be found for calculating optimum batch sizes.

IV. OPTIMIZATION MODEL

A. Writing an Optimization Model

The annual inventory holding cost for an item is the result of multiplying its yearly average inventory level by its annual holding cost per unit. As it was mentioned before, based on the information from the financial department, the inventory holding cost per unit for an article (PCB board) is defined as 10 percent of its value. Therefore, if the price of a board is represented by ***C***, its annual holding cost per unit can be expressed as $\boldsymbol{0.1 \times C}$. If 0.1 is denoted by ***(a)***, the expression can be written as $\boldsymbol{a \times C}$. By denoting the average inventory level for the same board as $\boldsymbol{I_{ave}}$, the annual inventory holding cost for that board can be calculated by $\boldsymbol{a \times C \times I_{ave}}$. This expression for one board can be extended to other boards too. By calculating the holding cost for each board and adding them together, the total inventory holding cost for all boards is obtained. If C_i represents the price of board (i) and $I_{ave,i}$ represents the average inventory level for board (i) , by having a 10 percent as a constant the total inventory holding cost for all the boards can be expressed as:

$$\text{Total inventory holding cost} = a \times C_1 \times I_{ave,1} + a \times C_2 \times I_{ave,2} + \ldots + a \times C_n \times I_{ave,n}$$

Where, (n) is the total number of boards: $i = 1, 2, 3, \ldots, n.$

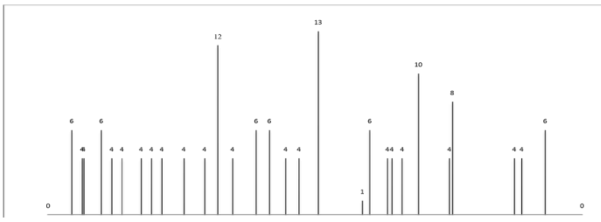
This expression can be turned to the objective function of a minimization problem:

$$\text{Minimize } Z = a \times C_1 \times I_{ave,1} + a \times C_2 \times I_{ave,2} + \ldots + a \times C_n \times I_{ave,n}$$

$$\text{for } i = 1, 2, 3, \ldots, n.$$

In order to find the optimum batch sizes for the boards, one can pursue the goal of minimizing the total inventory value of all boards. Since average inventory level for an item is in direct relation with its batch size, the $\boldsymbol{I_{ave}}$ for board i can be overwritten as a function of its batch size. As minimization tries to find the minimum value of Z, the optimal values for the batch sizes can be obtained. The only thing that remains is to find the relationship between each board's average inventory level ($\boldsymbol{I_{ave}}$) and its batch size. After that, by adding appropriate constraints, this objective function can be turned into a complete optimization model in Operations Research.

In order to find the relationship between $\boldsymbol{I_{ave}}$ for board **i** and its batch size, one should start from probing the annual demand pattern for each board. The annual demands for a few of the boards are illustrated in Figures below:



As it is clear from the charts, the demand has a lumpy nature. This pattern applies for all other boards too. If demand was continuous and steady, it would be easy to calculate the average inventory. So we have to make an assumption of a simplified demand d which is in agreement with the average value.

Assuming that the number of intervals "$\bar{t}$" for each cycle is equal to n, the average inventory for one cycle is equal to the area below the graph for that cycle divided by sum of all intervals, $n \times \bar{t}$. Since there is going to be the same cycle repeated over and over throughout the whole time scale, the average inventory level for the whole year is equal to the average inventory level for one cycle. Let us assume that the batch size is big enough to cover all the demand during n period and is exactly equal to the demand in that period: $x = n \times \bar{d}$.

Therefore:

$$I_{ave} = \frac{\bar{t}\times(x+(x-\bar{d})+(x-2\bar{d})+\ldots+(x-(n-1)\bar{d}))}{n\times\bar{t}} = \frac{nx-\bar{d}\times\frac{n(n-1)}{2}}{n} = x - \frac{\bar{d}n(n-1)}{2n} = x - \frac{\bar{d}(n-1)}{2}$$

Since, $x = n \times \bar{d}$, we have:

$$I_{ave} = x - \frac{x-\bar{d}}{2} = \frac{x}{2} + \frac{\bar{d}}{2}$$

In order to test the accuracy of this conclusion, some boards are randomly chosen and their average inventory level is calculated based on historical data. The results are shown in Table below:

Table 2. Calculations of Inventory Days

Date	Demand	Inventory level (batch size = 60)	Days in inventory	Inventory × Days
01-01-15	0	60	3	180
01-04-15	8	52	6	312
01-10-15	4	48	1	48
01-11-15	24	24	4	96
01-15-15	32	52	2	104
01-17-15	8	44	6	264
01-23-15	12	32	5	160
01-28-15	20	12	7	84
02-04-15	4	8	2	16
Historical average inventory			29.2	
Theoretical average inventory			36.9	

The Mean Absolute Percentage Error (MAPE) for the approximation of "I_{ave}" can be worked out as shown below:

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t-F_t}{A_t}\right| = \frac{100\%}{5}\left(\left|\frac{29.2-36.9}{29.2}\right| + \left|\frac{105.5-99.4}{105.5}\right| + \left|\frac{18.8-22.2}{18.8}\right| + \left|\frac{33.2-36.8}{33.2}\right|\right) = 15.27\%$$

Where At is the actual value and Ft is the forecasted value.

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Although this is not a very close approximation, it is good enough for continuing the calculations. Now that the value of I_{ave} has been expressed based on the batch size x and the average demand "$\bar{d}$", it can be replaced in the objective function of our minimization problem:

$$Minimize\ Z = a \times C_1 \times \left(\frac{x_1}{2} + \frac{\bar{d}}{2}\right) + a \times C_2 \times \left(\frac{x_2}{2} + \frac{\bar{d}}{2}\right) + \ \dots + a \times C_n \times \left(\frac{x_n}{2} + \frac{\bar{d}}{2}\right)$$

Since "a" is a constant and it is present in all the sentences, it can be taken away from the objective function without affecting the optimization result:

$$Minimize\ Z = C_1 \times \left(\frac{x_1}{2} + \frac{\bar{d}}{2}\right) + C_2 \times \left(\frac{x_2}{2} + \frac{\bar{d}}{2}\right) + \ \dots + C_n \times \left(\frac{x_n}{2} + \frac{\bar{d}}{2}\right)$$

$\frac{\bar{d}}{2}$ and C_i are also both constants and when they are multiplied with each other, they form another constant $\frac{\bar{d}}{2} \times C_i$. Since their value is fixed and they do not affect the optimization result, they can be taken away from the objective function too:

$$Minimize\ Z = C_1 \times \frac{x_1}{2} + C_2 \times \frac{x_2}{2} + \ \dots + C_n \times \frac{x_n}{2}$$

Nonetheless, "$\frac{x}{2}$" is a better approximation for average inventory level. By calculating the new MAPE for "$\frac{x}{2}$", the result will be:

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \left|\frac{A_t - F_t}{A_t}\right| = \frac{100\%}{5} \left(\left|\frac{29.2-30}{29.2}\right| + \left|\frac{105.5-90}{105.5}\right| + \left|\frac{18.8-20}{18.8}\right| + \left|\frac{33.2-30}{33.2}\right|\right) = 8.36\%$$

In addition, denominator 2 is also a common constant in all the expressions above and can be omitted. The final objective function will look like this:

$$Minimize\ Z = C_1 \times x_1 + C_2 \times x_2 + \ \dots + C_n \times x_n$$

Now that the objective function is prepared, the constraints should be added to complete the model.Within the available capacity, setups have a cost of zero. They create a cost when the capacity limit is violated and this week's orders have to be met next week. If the capacity is defined as the total time available for producing boards and performing setups, the constraint can be defined as shown below:

$$Total\ Production\ time + Total\ Setup\ Time\ \leq Capacity$$

If Di, is the total demand for board i and xi is the batch size, then the number of setups for board i is the ceiling function of their division. For example, demand of 100 and batch size of 30 requires a total number of $\left\lceil\frac{100}{30}\right\rceil = \lceil 3.33 \rceil = 4$ setups in total. By multiplying this number by the average setup time of 22 minutes – based on information from IFS – the total setup time for one type of board is calculated. For calculating the total production time, the total demand for each board has to be multiplied by its cycle time "$t_{pi(min)}$" (t_p denotes the cycle time, "i" denotes the board i and "min" says that the times are in minutes). For example, if the demand for a board is 100 units and cycle time "$t_{pi(min)}$" is two minutes, the total production time for that board is $100 \times 2 = 200$ min. The sum of these two times, for all boards should be less than or equal to available capacity in minutes "A_{min}". Mathematical expression of capacity constraint is shown below:

$$\sum_{i=1}^{n} \left(22_{min} \times \left\lceil\frac{D_i}{x_i}\right\rceil + D_i \times t_{Pi(min)}\right) \leq A_{min}$$

In order to complete the optimization model, the boundaries for the variables must be defined. All of the parameters in the objective function and constraint are constants except the batch sizes "x_i". These batch sizes cannot be greater than total demand for each board $x_i \leq D_i$. At the other hand, based on previous assumptions that where set over calculating the average inventory, each batch should be big enough to meet the average demand. This can be expressed as $x_i \geq \bar{d}_i$. Therefore, the boundaries for batches can be written as follows:

$$\bar{d}_i \leq x_i \leq D_i \qquad for\ i = 1, 2, 3, \dots, n$$

B. Final Model

The complete model with all its components is shown below:

$$Minimize\ Z = \sum_{i=1}^{n} C_i \times x_i$$

Subject to:

$$\sum_{i=1}^{n} \left(22_{min} \times \left\lceil \frac{D_i}{x_i} \right\rceil + D_i \times t_{Pi(min)} \right) \le A_{min}$$ And

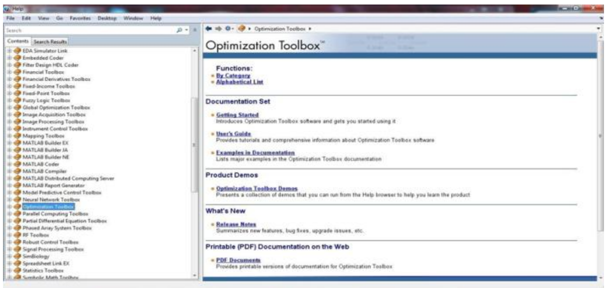
$$\overline{d}_i \le x_i \le D_i \qquad for\ i = 1, 2, 3, \ldots, n$$

V. SOLVING THE OPTIMIZATION MODEL

A way to solve an optimization problem using exact methods is MATLAB. MATLAB provides different toolboxes for various engineering fields.

A. Using MATLAB Optimization Toolbox

Here, the optimization toolbox is shown:



The next step is to choose a solver. MATLAB provides us with different options for different optimization problems. In order to choose a proper solver, MATLAB's Optimization Decision Table is used.

However, the solver fails to find an answer to this problem and responds with an error message. The reason for this failure is the constraint type of the problem. As it is clear from the table, *fmincon* is used for *smooth* linear or nonlinear constraints (general smooth). A smooth function is a function that has derivatives of all orders. Optimization solvers like those in optimization toolbox are derivative based. They are accurate and fast but they are designed to solve minimization problems that have *smooth* functions (functions that are continuously differentiable to some order) since they use derivatives to find direction of minimization (Mathworks.se, 2016). The constraint function of this problem is not smooth because of the term " $\left\lceil \frac{D_i}{x_i} \right\rceil$ ". Having the variable "x" in the denominator and inside the ceiling function makes the constraint function discontinuous and non-smooth in several points. The derivative of the function ceiling (x) is zero when x is not integer and is undefined when x is an integer number. As a result derivative based solvers in optimization toolbox are unable to solve such a problem. A simple version of the constraint function with only two variables is illustrated in Figure , to show the discontinuity of the function.

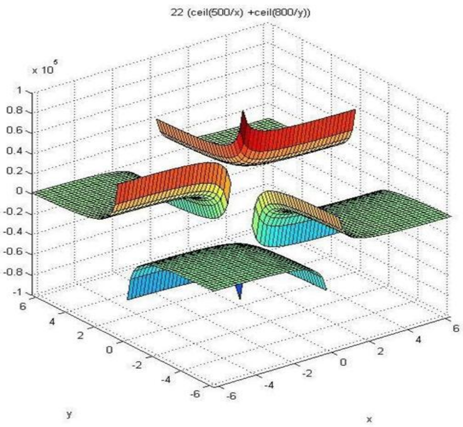
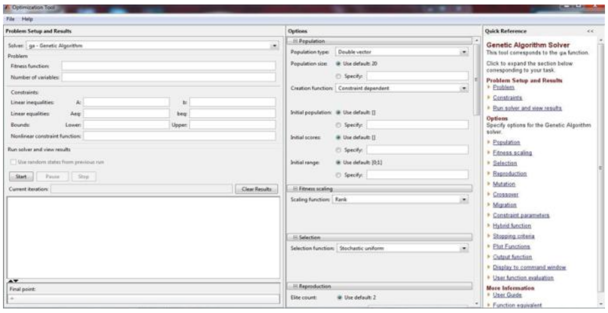


Fig 4: Discontinuity of Constraint Functions

With this attempt failing, the idea of solving the problem with exact methods should be put aside. The alternative is to use heuristic methods for finding a near optimum solution.

B. Heuristic Solution

As it was mentioned before, heuristic algorithms do not guarantee a global optimum solution but they provide an answer good enough in an acceptable amount of time. Fortunately, MATLAB has the ability to perform optimization using different heuristic solvers. The Global Optimization Toolbox in MATLAB is a tool that provides us with this opportunity.



As it is clear from above figure, the Optimization Tool requires many different input data for performing the optimization. In the solver text box, a series of different solvers are available Different settings give different answers when running the optimization. From experience it can be said that higher mutation rates result in faster and more optimum solutions since they increase the diversity of the solution population and help the algorithm search a wider area to find the optimum answer. After running the algorithm for several times, the best answer for batch sizes was chosen and modified to adapt to multiple lot sizes (the number of boards in each panel) so that the technical side of the problem is considered too.

C. Results

Boards	Multiple Lot Sizes	Lower Bound	Demand	Price	GA Solution	Final
X1	2	10	52	475.56	17.5	18
X2	2	4.8	24	338.64	12	12
X3	2	10	62	737.79	12.6	14
X4	2	4.18	92	504.09	18.6	20
X5	2	4.7	170	247.47	34.1	36
X6	3	6.33	133	315.06	33.4	36
X7	2	7.3	532	187.92	76.4	78

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X8	3	3	24	1016.43	3	3
X9	2	8.6	458	190.35	66.1	68
X10	2	9	36	462.48	12.2	14

The final result with the total inventory value of final batch sizes compared to current ones is shown in Table 10 below:

Table 3. Calculations of Final batch Sizes

The first column of the table simply indicates different boards. The second column, multiple lot sizes, is the number of boards in each panel. For example, if multiple lot size for a board is 6, there are 6 boards in each panel that goes through the production line. As a result, the batch size for this board can be 6, 12, 18, 24, etc. The third column, fixed values, is those boards that their lot size was predetermined as a fixed value so that they are not a decision variable anymore. The reason for these fixed values was discussed before. Fourth column is the lower bound for variables, meaning that the batch sizes cannot be less than this quantity. Lower bounds are the average demand quantity for each board. The fifth column is the modified annual demand for each board. Modified, meaning that the outlier data has been taken away. The sixth column is the price of each board. The seventh column is the current batch sizes for boards. The eighth column, GA Solution, is the answer given by MATLAB. This answer was obtained after running the optimization for several times and changing the settings in order to improve the optimal solution. The reason that problem is not solved with integer values and batch sizes are not complete integers is that it is much easier and faster for MATLAB to solve problems with continuous values than integer ones. These values had to be modified to comply with multiple lot sizes. The results are shown in column ninth, “Final”, as final optimum batch sizes.

The last row in the table shows the ratio of total inventory value resulted from new batch sizes over total inventory value resulted from current batch sizes. As it was mentioned before, the average inventory level for a board is considered to be half the batch size. At worst, it can be considered as a fraction of the batch size. However, when the total inventory values of new and current batch sizes are divided over to calculate the ratio, these constants cancel out. The formula used for calculating the ratio of total inventory value for two different batch sizes is shown below:

$$Ratio\ of\ Total\ Inventory\ Value = \frac{Constant \times \sum_{i=1}^{111} (New\ Batch\ Sizes \times Price)}{Constant \times \sum_{i=1}^{111} (Current\ Batch\ Sizes \times Price)}$$

$$= \frac{\sum_{i=1}^{111} (New\ Batch\ Sizes \times Price)}{\sum_{i=1}^{111} (Current\ Batch\ Sizes \times Price)}$$

As a result, the new batch sizes will reduce the total inventory value by 21.21% (100% - 78.79%).

VI. CONCLUSIONS

In this paper, the problem of finding the optimum batch sizes in a High mix, Low volume production line was investigated. The case was an SMT line producing a high mix of different circuit boards in different volumes. The first problem faced throughout the project was finding an alternative for EOQ method. Economic order quantities, traditionally used in many firms, were mainly developed for the purpose of inventory management and purchasing. Within those borders where there is a clear ordering cost including transportation, insurance and salaries for purchasing staff, the EOQ method makes perfect sense. Implementing the same principles in a different environment like production can mislead us enormously. Although many parameters like total demand and inventory holding costs are the same in both environments, the idea that setup cost is the proper equivalent of ordering cost in a procurement environment can lead us to many troubles. Setup costs are hard to measure in many cases and they are usually not fixed values. However, they are widely used in academic papers as a criterion for calculating the batch sizes. A good alternative for EOQ method was found to be OR models. By replacing setup cost with setup time and linking that time to the total available capacity, an OR model can be built that minimizes the inventory value and finds the optimum batch sizes.

REFERENCES

[1]Adacher, L. and Cassandras, C. (2013). Lot size optimization in manufacturing systems: The surrogate method. International Journal of Production Economics, p.1.
[2]Brannen, J. (1992). Mixing methods. 1st ed. Aldershot: Avebury.
[3]Chiu, S., Ting, C. and Chiu, Y. (2007). Optimal production lot sizing with rework, scrap rate, and service level constraint. Mathematical and Computer Modelling, 46(3), p.535.
[4]Coombs, C. (2008). Printed circuits handbook. 6th ed. New York: McGraw-Hill, pp.40.340.37.

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Vol. 3, Issue 3 , March 2016

[5]Creswell, J. (2009). Research Design. 1st ed. Thousand Oaks, California: SAGE Publications, Inc.
[6]Ferradás, P. and Salonitis, K. (2013). Improving changeover time: a tailored SMED approach for welding Cells. Procedia CIRP, 7, pp.598--603.
[7]Gest, G., Culley, S., McIntosh, R., Mileham, A. and Owen, G. (1995). Review of fast tool change systems. Computer Integrated Manufacturing Systems, 8(3), pp.205--210.
[8]Goubergen, D. and Landeghem, H. (2002). Rules for integrating fast changeover capabilities into new equipment design. Robotics and computer-integrated manufacturing, 18(3), pp.205--214.