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# Optimizing the Production Output Function in Dynamic Manufacturing Systems Using Genetic Algorithm

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**Abstract**

One of the main problems of the industrial society today is the low quality of products, the failure of products and systems, which causes problems at various levels of production and even causes catastrophic events for society and the environment. Weakness in dynamic manufacturing and production systems and weakness in optimizing these systems is an issue that needs to be addressed. Therefore, the main purpose of the present study is to answer some of these issues and problems in the statistical community. The researcher intends to analyze the issue as the main solution in the optimization of the output function of manufacturing systems. The problem was modeled by considering the constraints and assumptions set as nonlinear integer programming (MINLP). Then, to achieve the optimal global solution, using linearization techniques, the mathematical model of the problem was converted to linear integer linear programming (MILP). Based on this, the target function was examined using the genetic algorithm in MATLAB software and its results were presented for small, medium, and large dimensions for problem factories with different dimensions (sensitivity analysis).



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## Introduction

Production strategy, from Skinner's point of view, refers to some features of production as a competitive weapon (Skinner, 1969). Hayes and Will Wright define production strategy as a compatible decision-making model in production applications that is relevant to business strategy (Hayes and Wheelwright, 1984). Cox and Blackstone define production strategy as a comprehensive model of decisions that emphasize the formulation and utilization of production resources for maximum efficiency and must act in support of the company's overall strategic decisions and provide competitive advantage (Cox and Blackstone, 1998). Mills et al. stated that production strategy is a pattern of related decisions and actions, both structural and infrastructural in nature, which determines the capabilities of a company's production system and how it moves to achieve a set of production goals (Mills et al., 1995). In the literature, the production goals that a company sets as tools to compete in the market change from market to market and usually include quality, delivery, cost, flexibility and innovation, and more recently, environmental protection and after sales services are also added to the previous list. The determined goals should be translated into practical plans to be implemented. This process involves identifying and evaluating potential alternative actions that will lead us to our goals. Alternative actions include a heterogeneous combination of structural and infrastructural production decisions. Structural and infrastructural decisions can be suggested as two pillars of production strategy. The collection of structural decisions includes the process and technology for operations, and the infrastructure includes human resource policies, quality systems, organizational culture, and information technology (Hill, 1987). Infrastructure issues support structural decisions and are expanded through the insistence on day-to-day use with the commitment of senior management and work teams at all levels. They are imperceptible and expand over a period of time (Dangayach and Deshmukh, 2001). The first major work in the field of structural decisions (production process) belongs to Hayes and Wheelwright in their product / process matrix. They examined the process in both static and dynamic states. In static state, they believed that process selection depends on the producing environment, especially size of the production area, they showed how wrong divestiture can lead to poor production and trade performance, and they also stated that as the market evolves, the required processes also need to change (Voss, 2005). The fields of decision-making and related activities considered by Hayes and Will Wright can be classified in details as structural decisions which include quantity, duration and capacity time, size, time and infrastructure characteristics, automation equipment and process technology communications, integration type and level (vertical, horizontal, forward, backward, breadth and balance) and infrastructure decisions include human resources (skills, wage policies) quality measures (systems and controls), control procedures and production planning (Decision Rules, indirect processing technologies, centralization) and organization's general characteristics (structures, roles, mediators, and connectors) (Adamides and Pomonis, 2007).

Products that are processed by different types of production units may be manufactured in a range of diverse products or as a single product or as low standard products in large quantity. In fact, a large list of features is related to product's properties, process, workforce, materials, technology, and organization, which is referred to as production system (Skinner, 1969). (Hayes and Wheelwright, 1984 ; Hill, 1987) cited the importance of manufacturing as a source of competitive advantage in a manufacturing company. But most of the researches in this field have focused on the content of the production strategy and the relationship between several variables in this area, and less attention has been paid to optimization problems (Tan and Platts, 2004). The main goal of any process is improvement in determining the best conditions for operating process that provide optimal and desirable outputs simultaneously. Therefore, this simultaneous optimization with multiple responses is called "optimal multiple outputs" (Chen and Lu, 2007). Also in this stage, we may have multiple outputs with qualitative characteristics in each intermediate stage or in the final stage of multi-stage and multiple processes. In the final stage, outputs with appropriate quality characteristics are mainly influenced by the conditions of the entire operational stages and also depend on the diversity conditions of inputs and the qualitative characteristics of the outputs of the previous stage In other words, in each intermediate stage, the conditions of inputs and output characteristics can have a significant impact on the qualitative characteristics of the outputs of product's final stage (Colledani and Tolio, 2006). Therefore, this section assumes that the process performance in intermediate stages directly or indirectly affects the final product. In addition, the deviation from the specific objectives of the output values in the intermediate stage may directly and indirectly affect the outputs of different successive stages. Therefore, the internal dependence between the stages in and the manufacturing and production conditions is dynamic, which provides the characteristics of the outputs in the final stage of the manufacturing and production processes with the best qualitative characteristics of the final product (Fallahnezhad et al., 2016). Finally, it must be acknowledged that in controlling and optimizing the production's output function in dynamic manufacturing systems, two important points must be considered. First, to succeed in the experimental stage of the process, we must consider the input variables and the relationship between the input variables and the variables of the previous output in the in-stage modeling, and second, we must create the qualitative characteristics of the optimal product and the best conditions for all stages of the process in the optimization approach. Therefore, the purpose of this study is to develop a mathematical model to optimize the production's output function in dynamic manufacturing systems.

## Material and methods

From an optimization point of view, Jinn and Shi, proposed a model to integrate the variance error of each step in dynamic systems with multiple outputs (Jin and Shi, 1999). The model has a linear structure and the variance expansion is thought to be the result of deviations from the targets. Therefore, the proposed model provides a useful insight on different sources with effective product quality (Sasadhar Bera and Mukherjee, 2015). Another study by Zhou et al., and Liu et al., discusses the expansion of variance in several independent stations in the manufacturing process (Zhou et al., 2003; Liu et al., 2009). The nature of the study was basically related to a specific stage of the spatial model whose the main focus was to describe parts of the manufacturing process. However, in this model, the nonlinear relationship between input and output variables was not taken into account (Sasadhar Bera and Mukherjee, 2015). The researchers Shi, Zhou and Zantek et al., also proposed a systematic approach to measure the influence of the variability of the previous stage on the next stages as well as on the final stage of product in a correlated manufacturing scenario.

They identified the investment cost required to improve quality at each stage.

This model used the least squares estimation method to estimate the model parameters and its variance components. They also examined the deviation from the goal at each stage and studied the effect of the model on the variance in the final stage of product's qualitative characteristics. Their proposed approach distinguished the amount of variability of resources in the quality of the better product from optimization of the process parameter in different stages (Shi and Zhou, 2009 ; Zantek et al., 2002). Other researchers named Bowling et al., have determined the optimization processes of objective function using the appropriate Markov chain method to maximize the expected profits associated with manufacturing systems. Specific constraints were considered at the bottom and top of each step, and it was assumed that each qualitative characteristic would be calculated and controlled through normal distribution. In addition, this study required a 100% inspection of the appropriate cost of the expected information. In this study, waste reduction and reprocessing were on the agenda of these researchers in order to achieve optimal expected profit and target values in each stage and they showed sensitivity of waste and the cost of reprocessing on the expected profit. Assuming continued production, a 100% inspection, fixed cost of information and change in the process average are the key limitations of this study (Bowling et al., 2004). Finally, other researchers, such as Kwak et al., proposed a method to optimize manufacturing processes. They proposed to maximize the performances of each stage continuously from the first to the final stage, which again goes back to the initial stage. They take into account the relationships between the steps and their approach is in a way that specifies the conditions for optimizing the input variable without extracting the model's prediction (Kwak et al., 2010). In summary, Patient Rule Induction Method (PRIM) is used to examine the subfields of the input variable space for better output operations in order of priority from all domains. The PRIM acceptance method can be helpful for the space of high-dimensional input variables and has little sensitivity to data outputs. However, it depends on the number of observations with a lot of data. In addition, the method of accepting the Induction Rule is like a black box and has not yet provided a deeper study and insight into the variables of the manufacturing process. It also needs to confirm several models and prove the solution (Sasadhar Bera and Mukherjee, 2015). Because the subject has its own complexities in different stages of dynamic manufacturing systems, which creates a large number of independent and dependent variables in each stage and in the section under study, i.e. optimizing the product's output function in manufacturing systems, so the researcher has to use data analysis through various software such as MATLAB, etc. and employ different methods of optimizing functions such as genetic algorithm combination, which is one of the best optimization methods, in order to analyze and optimize the problem to achieve the goals of the study. The researcher intends to select one of the industrial companies of the country as the statistical population of the study in terms of its location and geographical position. In the qualitative part of data collection, non-random and judgmental samplings are used, for which we will use 25 experts for interviews and 10 experts for group discussions and meetings. In the quantitative part, all the data of the last 5 years, as daily data, will be sampled for one of the main production processes. In this research, in order to solve the proposed mathematical model and to solve the problem, the metaheuristic genetic algorithm (GA) is developed and then by providing a number of numerical examples, the performance of the proposed algorithm is evaluated. Due to the lack of standard data, several sample problems are randomly generated to test the performance of the proposed algorithms. The dimensions of each sample problem are determined by the number of factory facilities and the number of demands. In producing sample problems, the characteristics of the problem must be considered. In other words, sample problems must be generated in a way that is unsolvable. Based on what is specified in the concepts of model implementation on MATLAB, we must first provide the data under study, which is actually the data production, in order to obtain the results. The used algorithm starts from an initial answer and then moves in a loop to the answers in the vicinity. Using conditional commands, if the adjacent answer is better than the previous one, it will save that value. Otherwise it will keep its previous value and will go on to the next step and check the next condition. The purpose of this analysis is to calculate the production cost, production delay time and reduction of pollutants during the production sequence in a factory.

## Results

In this section, we present the output's results. The following figure is the result of the implementation of the genetic algorithm:

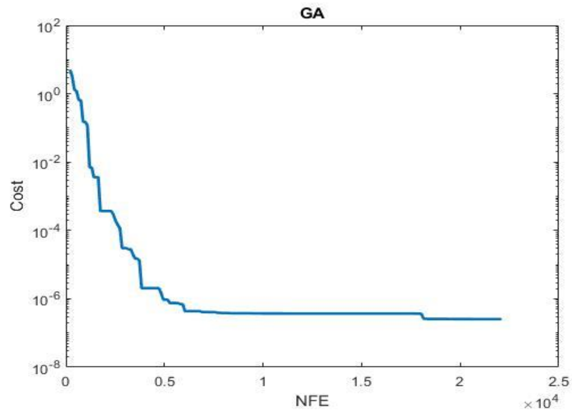


**Figure 2**. The result of the genetic algorithm

Based on the coding and the used algorithm, the best time and the best cost between the production system and the customers are known, and we considered this process to be equal to 5000 repetitions. As can be seen in the MATLAB program and in the command window, by repeating the processing, the cost goes through a reduction process until it puts the lowest value in the output in the 5000th repetition. In this program, we have examined different numbers of service providers and clients to view and compare detailed information in the output. To examine the work more closely, we have increased the coordinates of some of the points by a very large margin compared to the previously selected points, which led to an increase in customer service time as well as an increase in cost. To improve this situation, it is suggested to increase the number of service providers, which reduced the cost and time of servicing. In Tables 1 and 2, we examine 10 models in a small factory using the proposed algorithm:

**Table 1.** Samples and the number of products and orders in small, medium and large factories

| Sample | Number of orders | | | Number of products | | |
|---|---|---|---|---|---|---|
| | **Large** | **Medium** | **Small** | **Large** | **Medium** | Small |
| ۱ | ۲۵۰ | ۳۱ | ۱ | ۲۰ | ۶ | ۲ |
| ۲ | ۳۰۰ | ۳۵ | ۵ | ۲۰ | ۶ | ۲ |
| ۳ | ۴۰۰ | ۴۰ | ۷ | ۲۵ | ۷ | ۲ |
| ۴ | ۵۱۰ | ۴۵ | ۱۰ | ۳۰ | ۷ | ۳ |
| ۵ | ۶۰۰ | ۵۷ | ۱۲ | ۳۲ | .۸ | ۳ |
| ۶ | ۶۵۰ | ۶۱ | ۱۷ | ۳۸ | .۸ | ۴ |
| ۷ | ۷۳۰ | ۶۵ | ۲۰ | ۴۱ | ۹ | ۴ |
| ۸ | ۸۰۰ | ۷۰ | ۲۳ | ۴۵ | ۱۲ | ۴ |
| ۹ | ۹۰۰ | ۷۵ | ۲۷ | ۵۰ | ۱۴ | ۵ |
| ۱۰ | ۱۰۰۰ | ۸۰ | ۳۰ | ۶۰ | ۱۶ | ۵ |

**Table 2.** Results of delay time, total cost and emission of pollutants in small, medium and large factories (genetic algorithm)

| | CO2 emission (ppm) | | | Total cost of system ($) | | | Time (second) | | |
|---|---|---|---|---|---|---|---|---|---|
| **Sample** | **Large** | **Medium** | **Small** | **Large** | **Medium** | **Small** | **Large** | **Medium** | Small |
| ۱ | ۱۳۵۵ | ۱۱۷۸ | ۳۵۰ | ۱۰۱۲۵۴ | ۳۷۵۹۹۵ | ۱۰۰۲۵۴ | ۶۸/۵۴۲ | 8.6652 | 2.35 |
| ۲ | ۱۳۶۵۸ | ۱۲۰۸ | ۳۸۴ | ۱۱۲۳۵۲ | ۳۷۹۵۵۱ | ۱۳۵۵۶۲ | ۷۲/۳۳۲ | 11,472 | 4.65 |
| ۳ | ۱۴۰۰۲ | ۱۳۲۱ | ۳۹۹ | ۱۶۳۲۵۱ | ۴۰۴۱۲۴ | ۱۴۶۸۸۲ | ۸۱/۴۰۲ | 15.985 | 6.998 |
| ۴ | ۱۴۲۳۰ | ۱۳۴۲ | ۴۵۰ | ۱۷۵۸۹۵ | ۴۲۳۵۵۴ | ۱۷۹۳۰۲ | ۸۸/۴۸۴ | 18.663 | 7.885 |
| ۵ | ۱۵۲۰۰ | ۱۵۷۴ | ۴۵۹ | ۱۸۸۵۴۷ | ۴۶۸۵۹۶ | ۱۸۱۳۳۲ | ۹۰/۴۴۱ | 29.874 | 9.551 |
| ۶ | ۱۶۲۱۰ | ۱۶۲۲ | ۶۳۲ | ۱۹۲۳۳۲ | ۴۹۶۵۵۴ | ۲۳۱۰۲۱ | ۹۳/۲۲۱ | 32.412 | 13.74 |
| ۷ | ۱۶۸۹۰ | ۱۷۰۰ | ۸۸۵ | ۲۰۲۱۱۴ | ۵۲۱۴۴۷ | ۲۴۹۷۰۴ | ۹۵/۳۳۲۵ | 39.994 | 16.475 |
| ۸ | ۱۷۵۳۲ | ۱۷۶۵ | ۹۳۵ | ۲۱۸۷۴ | ۵۴۷۷۵۸ | ۲۶۵۹۹۵ | ۹۹/۷۱۸ | 42.412 | 19.77 |
| ۹ | ۱۸۰۵۰ | ۱۹۳۲ | ۱۰۰۲ | ۲۲۹۶۶۳ | ۵۹۸۶۶۴ | ۲۹۷۳۰۲ | ۱۰۲/۳۳۲ | 48.99 | 23.542 |
| ۱۰ | ۱۹۸۵۰ | ۲۱۲۰ | ۱۰۲۷ | ۲۳۶۵۶۲ | ۶۳۵۹۷۵ | ۳۰۲۶۶۵ | ۱۱۰/۴۷۵ | 51.062 | ۲۸/۱۰۲ |

Comparative diagrams of cost, time, and pollutants of genetic algorithms in small, medium, and large factories are shown in Figures 3 to 5.

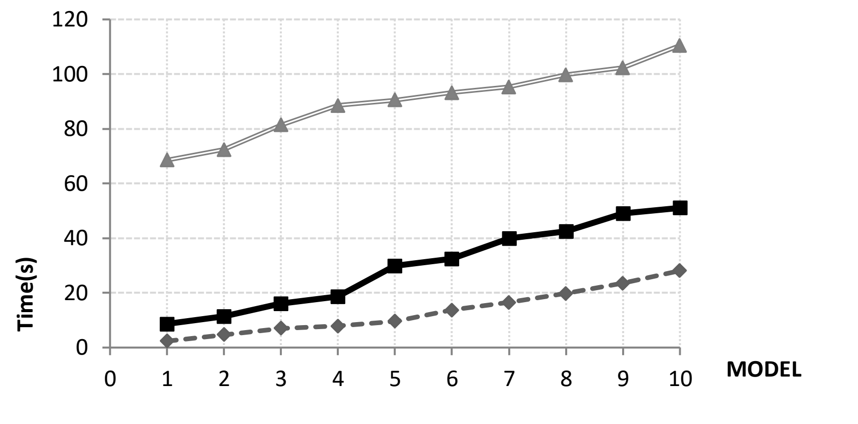


**Figure 3.** Comparison of total system execution time using genetic algorithm

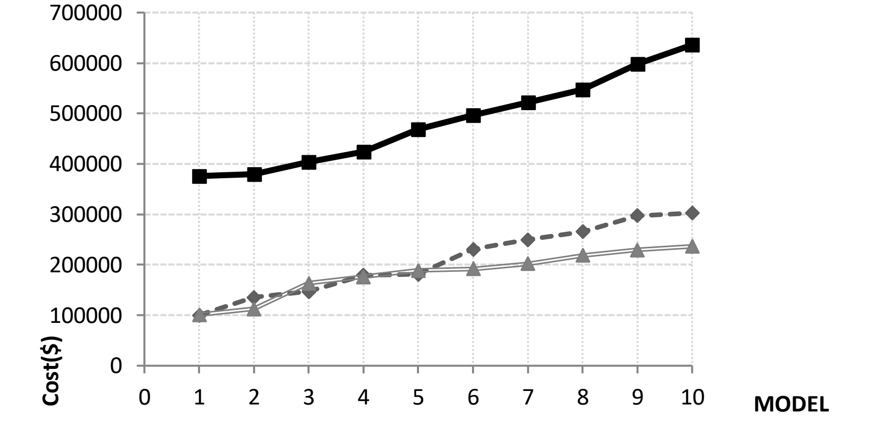


**Figure 4.** Comparison of total system cost using genetic algorithm

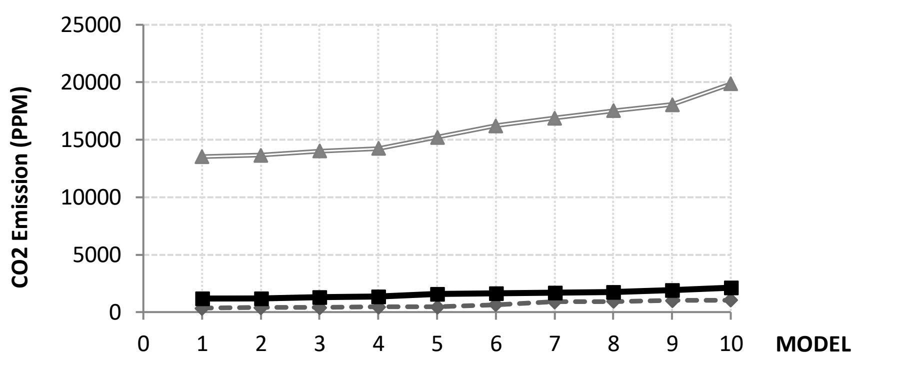


**Figure 5.** Comparison of carbon dioxide emissions using genetic algorithm

Given that the rejection or acceptance of projects is the most important component of an investment, the main parameters must be analyzed in order to obtain acceptable amount of change. In the meantime, considering the issues of engineering economics, the time value of money should also be taken into account. Therefore, sensitivity analysis should be done in conjunction with engineering economics methods, the most important of which is to consider the present value of the investment and the rate of return on investment. In order to analyze the sensitivity, we examine the model for the factory with small, medium, and large measurements. We review the results of the genetic algorithm for time, carbon dioxide emissions and cost.

**Table 3.** Results of time, cost and CO2 emission

| Size | Item | GA | | |
|---|---|---|---|---|
| Small | | Cost | Emission | Time |
| | ۳ | ۱۱۵۵۰ | ۱۴۱۵۲ | ۳/۸۵۴ |
| | ۶ | ۱۳۴۵۴ | ۱۶۳۳۲ | ۵/۱۰۲ |
| | ۸ | ۱۸۰۴۷ | ۱۷۱۲۰ | ۷/۹۶۸ |
| Medium | ۱۲ | ۲۳۶۶۵ | ۲۰۳۵۲ | ۱۱/۰۲۱ |
| | ۱۶ | ۲۴۱۴۱ | ۲۴۶۶۵ | ۱۵/۰۰۱ |
| | ۱۸ | ۲۷۸۹۸ | ۲۶۶۸۱ | ۱۷/۲۳۲ |
| Large | ۲۰ | ۳۰۶۵۲ | ۲۸۹۶۸ | ۲۰/۳۸۴ |
| | ۲۴ | ۳۴۸۷۵ | ۳۲۰۷۸ | ۲۶/۳۶۳ |
| | ۲۸ | ۳۷۷۴۵ | ۳۴۵۸۵ | ۲۹/۸۸۵ |

## Discussion

In order to plan production tactically, it will be very useful and productive to distinguish between scheduling and planning. In planning activities, we have integrated planning and allocation of gross production to factories or production lines. We also analyze uniform capacity decisions, such as allocating work to qualified second-hand contractors or an active production line. But it is worth noting that they do not involve successive decisions. In this study, considering the limitations of time windows, the problem of product production in dynamic manufacturing systems was investigated with the aim of minimizing total system costs, product transfer time and pollution.

For this purpose, after studying the sources and references related to the design of manufacturing systems, the problem under study was modeled as Mixed Integer Non Linear Programming (MINLP) while considering the constraints and assumptions. Then, in order to achieve the optimal global solution, using linearization techniques, the mathematical model of the problem was converted to Mixed Integer Linear Programming (MILP). Accordingly, the intended objective function was investigated using a genetic algorithm on MATLAB and its results for different measurements (small, medium and large) were presented to manufacturing factories (sensitivity analysis)

## Conclusions

By examining the result of the genetic algorithm, we can conclude that we were able to achieve the best time and the best cost between the producer and the customer. The best created state will reach its best after 250 repetitions. Sensitivity analysis was done on three different factories with small, medium and large model sizes using genetic metaheuristic algorithms on MATLAB. As the size of the problem increases, the exact solution time of the proposed mathematical model increases dramatically. Therefore, in order to solve problems with medium and large sizes, two genetic metaheuristic algorithms were developed. The results obtained from solving small-scale problems by the proposed algorithms showed that each of these algorithms has the necessary efficiency to solve small problems. Then, the performance of the proposed algorithms in solving medium and large problems was compared. It should be noted that the three criteria of criteria, carbon dioxide emissions and delay time in both methods were evaluated and in reviewing all the results, it is clear that the genetic algorithm easily optimizes the cost and time in this study under better and faster conditions.

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