OPTIMIZATION OF MANUFACTURING PROCESS USING GENETIC ALGORITHM BY OPTIMAL MACHINE COMBINATION: MATLAB SIMULATION & RESULTS

Sharad Kumar Rathore and Pushyamitra Mishra
Department of Mechanical Engineering, Maulana Azad National Institute of Technology, Bhopal, India

ABSTRACT

Quality production in quantity of sophisticated product requires huge investment. The manufacturing process must be cost effective up to the optimal threshold to sustain the product in international market. These conditions can only be achieved by optimizing the manufacturing process. The focus of the presented research paper is to determine the optimal combination of the machines to avoid buffering and bottleneck condition in the manufacturing process. The individual parameters of machine participating in manufacturing process at cluster level are incorporated in mathematical model to obtain a resultant objective function of complete manufacturing process. Genetic algorithm is implemented on resultant objective function to decide optimal set of machine combination. Simulation is carried in Matlab Software. Simulations results are compared with existing combination and found that overall efficiency and performance has been improved up to remarkable extend.

Keywords: Genetic Algorithm, Manufacturing Process Matlab Simulation, Optimal Machine Combination,


http://www.iaeme.com/IJMET/issues.asp?JType=IJMET&VType=9&IType=6

1. INTRODUCTION

Production efficiency of any industrial installation plays an important role in the success of any company or corporate. Rapid transportation and fast communication has encouraged manufacturer from across the world for remote business opportunities. The situation demands maximum efficiency with minimum investment means maximum & optimal utilization of
available resources of the company. Enhancement in the efficiency and overall performance of manufacturing systems to achieve better output by first identifying the problem and then focusing on key parameters which are responsible for the same is the objective of the research work. Productivity of plant integrates numbers of factors as depicted in the figure-1 below.

![Figure 1](embedded_image)

**Figure 1** Key Factors affecting Productivity of a Manufacturing Plant

The production process [1] must be cost effective up to the optimal threshold to sustain the product in international market. These conditions can only be achieved by optimizing [2] the production process. Numbers of factors affecting the production process are floor design, supply chain management, healthy work environment and optimal selection of machine combination [3]. Among these factors; our research focuses on the optimal combination of machines to be installed.

In this paper we have presented discrete-event simulation technique and with the help of which we have carry out designing and modeling of the existing manufacturing systems and visualized the critical areas and identified important parameters which are responsible for dynamic issues of total efficiency in the manufacturing systems. Different methodologies used in a production process have been summarized for the purpose of production improvement and to smooth the production flows and ultimately raise overall productivity & quality of the installation [4]. The contemporary framework used in the overall production improvement techniques which has got numerous parameters like supply chain management which deals between different suppliers and the availability of limited products in stock thereby making it necessary to take care and focus on the issues of production disturbance reduction methodologies. The presented paper is primarily based on three main or fundamental stages these are (1) initial planning and data gathering (2) critical analysis and implementation at the base level and (3) continuous improvement through feedback and control. We have develop overall objective function of complete manufacturing process of existing plant, Genetic Algorithm [5] is implemented on overall objective function for optimal solution. The objective is to find out optimal combination of participating machines to avoid starving and bottleneck condition. Genetic Algorithm is basically a computational method that optimizes an objective function of mathematical problem by iteration to improve a feasible solution. Different optimization techniques are also discussed like, Particle Swarm Optimization [6], Ant Colony Optimization [7] and Differential Evaluation Optimization [8].

### 1.1. CHARACTERISTICS OF AN IDEAL MANUFACTURING PLANT

Regardless of the nature of the manufacturing organization or the product being manufactured, all manufacturing systems have a number of common characteristics, which are:

1. System must be cost-effective & must work on threshold optimization
2. System must consist of an set of sub-systems instead of composite one
3. Systems must be capable of controlling sub-systems & overall system
4. Systems need a flow of information and a decision-making process
1.2. OBJECTIVE OF SYSTEM DESIGN
Application of Genetic Algorithm needs to achieve specific parameter which are listed below to obtain and Ideal manufacturing system:

1. Minimize the total time taken & set-up costs of every manufacturing unit
2. Minimize the mean time in the shop, Minimize the machine idle time
3. Minimize the mean number of jobs & mean queue time in manufacturing process
4. Remove starving condition & bottleneck condition in manufacturing process
5. The system must work on threshold Optimization

Above specifications are milestone to be achieved while designing a manufacturing system. The research problem can be defined by generating an optimal set of machine combination by the application of Algorithm for maximum utilization, minimum starving & bottleneck condition in the production process for maximum productivity. An approach has been presented in the paper to meet the above specification and to make system optimized by implementation of Genetic Algorithm.

2. LITERATURE SURVEY
Research Scholars from across the world had carried out research to optimize the floor design of a manufacturing plant. In the following text we had quoted few recent important research in the concerning field.

R. K. Phanden and H. I. Demir [9] in year 2018 concluded in that the arrangement or layout of resources plays the cardinal role to improve optimum utilization of these resources. The layout of these facilities in the shop floor is directly related with profit & productivity. The facility layout strategies are truly connected with both the quality and cost of the product. The objective of research article was the production of high quality product by GA for optimal use of resources.

Xiaobing Liu & Hongguang Bo, China [11] in year 2017 presents optimization approach based on genetic algorithm is tested on typical production management problems in hybrid distributed manufacturing execution system. The results are compared with other proposed approaches.

Yi-Chang Li; Seung Ho Hong, China [12] in year 2017 presents a case study, which shows that the proposed algorithm reduced the load demand during an RT-DB event, increasing the manufacturer's profits. Furthermore, the relationship between the incentive rate and the demand elasticity of the consumer, as well as the production volume and profits is described.

H. Shishangiya and M. Bandyopadhyay, India [13], year 2017 discusses the FEA-based engineering design, simplified manufacturing design, manufacturing experience with highlighting quality control, and the system integration activities undertaken for the TWIN source test facility.

Xingquan Zuo & Alice E. Smith, China [14], year 2016 states that genetic algorithm effectively identifies the set of non-dominated machine sequences, while the linear program uses the relative assignments obtained by the genetic algorithm to determine optimal absolute machine locations.

Necip Baris Kacar; Reha Uzsoy, USA [15], year 2015 in year 2015 implement a gradient-based simulation optimization approach, the Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm, to estimate clearing functions (CFs) that describe the
expected output of a production resource as a function of its expected workload from empirical data.

Kung Jeng Wang & Shih-Min Wang, Taiwan [16], year 2012 states that the Capacity planning deals with the conflicts among multiple factories. This paper makes a contribution in successfully building a negotiation-based capacity-planning model applied to a multiple-factory environment. The outcome of the experiments shows the efficiency of the proposed model and the effect of different negotiation attitudes

Andreas Klemmt & Gerald Weigert, Germany [10] in year 2010 elaborates that the bottleneck condition in manufacturing process is the photolithography area because of its highly expensive tools and complex resource constraints. The objected goals are the maximization of throughput, the minimization of setup costs and a balancing of machine utilization.

2.1. RESEARCH GAP

Following table presents relevant research papers from across the globe in the concerning topic. The table also elaborates about the research finding, conclusion and research gap in the field of facility planning optimization.

<table>
<thead>
<tr>
<th>No</th>
<th>Research Title, Year, Authors’</th>
<th>Findings and Conclusion</th>
<th>Research Gap</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Integrated bacteria foraging algorithm for cellular manufacturing in supply chain considering facility transfer and production planning by C. Liu &amp; J. Wang, China Elsevier-AppliedSoft Computing, Volume 62, January 2018, pp 602-618 [18]</td>
<td>The integrated bacteria foraging algorithm embeds a heuristic and evolution operators. The superiority of proposed algorithm over other meta-heuristics is illustrated. Facility transfer and production planning decisions are made simultaneously.</td>
<td>The stopping criteria of tracking the improvement of OFV deserve test. Algorithm is stopped when the standard deviation of OFV in the population is less than an arbitrary small constant, or when the optimal OFV in population remains unchanged for several times continuously</td>
</tr>
<tr>
<td>2</td>
<td>Visually enhanced situation awareness for complex manufacturing facility monitoring in smart factories Fangfang Zhou &amp; Xiaoru Lin-China Elsevier-Journal of Visual Languages &amp; Computing, Volume 44, February 2018, Pages 58-69 [19]</td>
<td>Presents qualitative &amp; quantitative situation assessment model. &amp; an informative visual analysis system that support RHK’s monitoring &amp; troubleshooting in smart factories. The result shows effectiveness &amp; prospects its possible inspiration for other similar scenarios in complex manufacturing facility monitoring in smart factories.</td>
<td>It is expected to extend the system to situation awareness of a whole production line when process data acquisition of other parts is ready. The possibility of applying visual analytics to long-term historical process data analysis for process optimization and manufacturing innovation is yet to be worked.</td>
</tr>
<tr>
<td>3</td>
<td>&quot;Hybrid manufacturing – integrating traditional manufacturers with additive manufacturing (AM) supply chain&quot; Elsevier-Additive Manufacturing, Volume 21, May 2018, Pages 159-173 D. Strong &amp; M Kay-USA [20]</td>
<td>A hybrid manufacturing supply chain based on metal Additive Manufacturing (AM) is proposed. Uncapacitated Facility Location and p-median models are applied to identify the optimal location. Traditional Small and Medium Enterprises (SME) can participate in evolving AM supply chain by offering post-processing services via Hybrid-AM.</td>
<td>Adding capacity to existing AM hubs is preferred over establishing new AM hubs at current demand is yet to be researched. Residual stress relieving stage prior to machining, incorporating product-mix models with different types of post-processing needs and time-sensitivity yet to be included. Study did not include local factors such as availability of AM supplies, operators and policies that could affect the proposed AM hubs.</td>
</tr>
<tr>
<td>4</td>
<td>Optimal planning of EV charging network based on Multi objective decision making model is proposed, with two Boundry Condition for Genetic Algorithm is not deciding which</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
3. OPTIMIZATION TECHNIQUE

Most commonly used Heuristic methods in the optimizing the layout design are Tabu Search (TS), Simulated Annealing (SA), Differential Evaluation (DE) and Genetic Algorithms (GA). Popularity of heuristics search technique has flourished in the recent years and published studies may be found in literature in journals. R. Arostegui al classifies the heuristics technique into tailored & general. Tailored heuristics have limited applicability to specific problem, general algorithms address strategy to obtain the approximate solutions thus are widely applicable in various forms of the combinatorial optimization. A brief information is presented about most commonly used optimization technique in the below text.

3.1. TABU SEARCH

Tabu Search [23] commonly refer as TS is mathematical optimization method which belonging to class of the local search techniques. The tabu search improves performance of local search method with the use of memory structures; a potential solution has been determined by its application. This is marked as taboo so that algorithm does not visit possibility repeatedly. Tabu search uses a local or neighborhood search procedure to iteratively move from one potential solution x to an improved solution x’ in the neighborhood of x, until some stopping criterion has been satisfied which is generally, an attempt limit or a score threshold. In order to avoid these pitfalls and explore regions of the search space that would be left unexplored by other local search procedures, tabu search carefully explores the neighborhood of each solution as the search progresses. The solutions admitted to the new neighborhood, N(x), are determined through the use of memory structures. Using these memory structures, the search progresses by iteratively moving from the current solution x to an improved solution x’ in N(x).

3.2. SIMULATED ANNEALING

Simulated annealing [24] that is SA is a probabilistic technique for approximating the global optimum of a given function. Specifically, it is a metaheuristic to approximate global optimization in a large search space. It is often used when the search space is discrete. For problems where finding an approximate global optimum is more important than finding a precise local optimum in a fixed amount of time, simulated annealing may be preferable to alternatives such as gradient descent. The name and inspiration come from annealing in metallurgy, a technique involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects. Both are attributes of the material that depend on
its thermodynamic free energy. The simulation can be performed either by a solution of kinetic equations for density functions or by using the stochastic sampling method. At each step, the simulated annealing heuristic considers some neighboring states of the current state s, and probabilistically decides between moving the system to states or staying in-state s. These probabilities ultimately lead the system to move to states of lower energy. Typically this step is repeated until the system reaches a state that is good enough for the application, or until a given computation budget has been exhausted.

3.3. DIFFERENTIAL EVALUATION

Differential evolution [8] is a method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. Such methods are commonly known as meta-heuristics as they make few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. Howeve DE can therefore also be used on optimization problems that are not even continuous, are noisy, change over time. DE optimizes a problem by maintaining a population of candidate solutions and creating new candidate solutions by combining existing ones according to its simple formulae, and then keeping whichever candidate solution has the best score or fitness on the optimization problem at hand. In this way the optimization problem is treated as a black box that merely provides a measure of quality given a candidate solution and the gradient is therefore not needed.

4. GENETIC ALGORITHM

The genetic algorithm [25] is a method for solving both constrained and unconstrained optimization problems that is based on natural selection, the process that drives biological evolution. The genetic algorithm repeatedly modifies a population of individual solutions.

4.1. ADVANTAGES OF GENETIC ALGORITHM

Following are the advantages offered by implementation of Genetic Algorithm which makes it choice for research scholars:

1. Genetic algorithms search parallel from a population of points. Therefore, it has the ability to avoid being trapped in local optimal.
2. Genetic algorithms use probabilistic selection rules, not deterministic ones.
3. Genetic algorithms work on the Chromosome, which is encoded version of potential solutions’ parameters, rather the parameters themselves.
4. Genetic algorithms use fitness score, which is obtained from objective functions, without other derivative or auxiliary information

4.2. LIMITATIONS OF GENETIC ALGORITHM

1. Take long time to reach to convergence
2. No guarantee of finding global maxima. But then again, apart from brute force, there is rarely any guarantee
3. Totally depends upon trial and error technique, nothing can be controlled during optimization process
4. Complex Technique
5. Incomprehensible solutions
5. MANUFACTURING SYSTEM

Manufacturing system can be defined as a conglomeration of elements that has the ability and the capacity to process or convert available raw materials into some products of final or intermediate use. In general a system is an arrangement or assembly of inter-dependent processes or activities that are based on some logic functions. It operates as a whole and is designed or builds with an intension to achieve desired objectives. Therefore, manufacturing is ‘adding value’ to the material. The value added to the material through processing must be greater than the cost of processing to allow the organization to make money or a profit. Therefore, added value can be defined as the increase in market value resulting from an alteration of the form, location or availability of a product, excluding the cost of materials and services.

Our objective is to analyze a manufacturing system and then compare it with an alternative system of manufacturing to develop a feasible solution. The performance indicators to evaluate and compare a manufacturing system are:

1. Throughput ($\delta t$): Number of lots that leave the manufacturing system per unit time,
2. Flow time ($t_f$): Time that is taken by a lot to travel through the complete system
3. Coefficient of variation of flow time ($c_r$): Net amount of variability in flow time of a lot in manufacturing system to complete its process
4. Utilisation ($u_t$): Fraction of time when the a machine is busy in processing lots
5. Work-in-process or wip ($wip$): Number of lots (size) in a manufacturing system to carry out the operations.
6. Raw process time ($t$): Time taken to work upon raw material to convert into finished product.

http://www.iaeme.com/IJMET/index.asp 325  editor@iaeme.com
Optimization of Manufacturing Process Using Genetic Algorithm by Optimal Machine Combination: Matlab Simulation & Results

To analyze a manufacturing system, we need to model it and determine its performance. For simple plants we collect data and apply queuing equations for accurate calculations. But these queuing equations have limited range of validity. When plants become complex, we need advanced queuing theory along with the theory of stochastic process. However such modeling requires substantial effort and extensive mathematical inputs, with a limited applicability range. Hence we switch over from analytical models to the field of simulation. The figure tries to illustrate the different stages in the design process and the data required and its range of applicability for analysis.

![Figure 4 Mathematical Tools for System Analysis](image)

Flow line of manufacturing process is one of the important aspects which needed to be understood in comprehensive aspect. A flow line is the path of the material on which the material flows and values are added on the material either by process or by peripheral addition. We need to determine the mean throughput and flow time per lot type and the utilization per machine. Types of flow line are as listed below in the table.

**Table 2 Types of Flow Line**

<table>
<thead>
<tr>
<th>No</th>
<th>Configuration</th>
<th>Descriptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>Flow Line</td>
<td>The Machine and Buffers are placed on straight line</td>
</tr>
<tr>
<td>02</td>
<td>Flow Line with by passing</td>
<td>Some Lots skips some of the operation</td>
</tr>
<tr>
<td>03</td>
<td>Flow line with backtracking</td>
<td>Some lots revised few of the operation as per need</td>
</tr>
<tr>
<td>04</td>
<td>Parallel Machines</td>
<td>Some lots bifurcate the flow line and join the same line after few operation</td>
</tr>
<tr>
<td>05</td>
<td>Converging flow line</td>
<td>Two or more line converges after execution of certain events</td>
</tr>
<tr>
<td>06</td>
<td>Diverging flow line</td>
<td>Lots follow single line and the bifurcate after that in two or more line</td>
</tr>
</tbody>
</table>

6. MATHEMATICAL MODEL OF SYSTEM

The Mathematical Model of a manufacturing or production system can be defined as mathematical description of system facilities, embedded machineries, process, system event, applications, raw material characteristics, design and condition with coordinates of system in state space using mathematical concepts and language. The process of developing a mathematical model is termed as mathematical modeling. Mathematical models so developed are used in the simulation, design and optimization of specific application for efficiency, performance and reliability improvement. The mathematical model of a manufacturing system is incorporates (1) Type of a Production System (2) Models of Machines (3) Models of Material Handling Devices (4) Rules of Interactions (5) Performance Measures
7. MATHEMATICAL MODELS OF MACHINES
The first stage in mathematical modeling process, the expert must start with the modeling of standalone machine at cell level, followed by modeling at cluster level, then module level and then on the complete process level. Following parameters are needed to be focus and supposed to be taken into the account in module:

**Cycle Time (T):** Time necessary to process a part by a machine. The cycle time may be constant, variable, or random.

**Machine Capacity (c):** Number of parts produced by specific machine per unit of time; when the machine is up is Machine Cycle.

**Slotted Time:** The time axis is slotted with slot duration equal to the cycle time.

**Un-Slotted Time:** The above mentioned changes may occur at any time moment. If the cycle times of all machines are identical, such a system with a slight abuse is still referred to as synchronous. If the cycle times are not identical, the system is called asynchronous.

8. CASE STUDY
The automotive ignition manufacturing system has been taken a case study in our research work. Ignition Coils supply the required level of electrical energy essential to ignite air & fuel mixtures in specific ratio in a combustion chamber of power engine. Coils are designed to achieve wide variety of evolving requirements for the combustion calibrations. Different types of automotive ignition coil assemble are available as (1) Pencil coils (2) Plug top coils (3) Coil-near-plugs (4) Waste spark systems. The integral and important part of the assemble system is as listed below:

<table>
<thead>
<tr>
<th>01</th>
<th>Insulating Cover</th>
<th>06</th>
<th>Housing</th>
</tr>
</thead>
<tbody>
<tr>
<td>02</td>
<td>Magnetic Core</td>
<td>07</td>
<td>Winding Layer</td>
</tr>
<tr>
<td>03</td>
<td>Primary Coil</td>
<td>08</td>
<td>Light Weight Sheet</td>
</tr>
<tr>
<td>04</td>
<td>Secondary Coil</td>
<td>09</td>
<td>Mould compound</td>
</tr>
<tr>
<td>05</td>
<td>Insulating Body</td>
<td>10</td>
<td>High Voltage Connecting Conductor</td>
</tr>
</tbody>
</table>

There are mainly two parts which are imported from other manufacturing company that is (1) Microprocessor (2) Microprocessor Software Program (3) Ignition System. Following is the list of process which will be took place during the manufacturing of the Embedded Smart Ignition Coil:
Table 4 List of Process in manufacturing of Smart Automatic Ignition System

<table>
<thead>
<tr>
<th>Notation</th>
<th>Operation Detail</th>
<th>Notation</th>
<th>Operation Detail</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>Foundation Manufacturing</td>
<td>06</td>
<td>High Voltage Transformer Molding</td>
</tr>
<tr>
<td>02</td>
<td>Foundation Insulation Covering</td>
<td>07</td>
<td>Ignition System Integration</td>
</tr>
<tr>
<td>03</td>
<td>Magnetic Core Manufacturing</td>
<td>08</td>
<td>Smart Card Integration</td>
</tr>
<tr>
<td>04</td>
<td>Primary Coil Winding</td>
<td>09</td>
<td>Assemble Insulation</td>
</tr>
<tr>
<td>05</td>
<td>Secondary Coil Winding</td>
<td>10</td>
<td>Testing and Packaging</td>
</tr>
</tbody>
</table>

8.1. SYSTEM DISCRIPTION

The production system for the smart automatic ignition system under consideration is shown below. It consists of 10 operations. These operations are referred as Operation_1, Operation_2, Operation_3, Operation_4, Operation_5, Operation_6, Operation_7, Operation_8, Operation_9, and Operation_10.

The Operations are as listed in the table below:

Table 5 List of Operations in manufacturing of Smart Automatic Ignition System

<table>
<thead>
<tr>
<th>Notation</th>
<th>Operation Detail</th>
<th>Notation</th>
<th>Operation Detail</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operation_1</td>
<td>Foundation Manufacturing</td>
<td>Operation_6</td>
<td>Transformer Molding</td>
</tr>
<tr>
<td>Operation_2</td>
<td>Foundation Insulation Covering</td>
<td>Operation_7</td>
<td>Ignition System Integration</td>
</tr>
<tr>
<td>Operation_3</td>
<td>Magnetic Core Manufacturing</td>
<td>Operation_8</td>
<td>Smart Card Integration</td>
</tr>
<tr>
<td>Operation_4</td>
<td>Primary Coil Winding</td>
<td>Operation_9</td>
<td>Assemble Insulation</td>
</tr>
<tr>
<td>Operation_5</td>
<td>Secondary Coil Winding</td>
<td>Operation_10</td>
<td>Testing and Packaging</td>
</tr>
</tbody>
</table>

9. MATHEMATICAL MODEL OF SYSTEM

The common notation used in the forth coming text is as denoted below:

1. Machine Costs = CCOST_PARAMETER in Unit Currency
2. Machine Capacity = μij Parts per unit time
3. Tool capacity per Machine Cost = Uij in Parts Unit per operational Slot
4. Throughput = λi per unit time, Slot Duration = τ
5. Productivity of Machine = ρ products Unit per operational Slot

Consider a serial production line with M exponential machines denoted as

\[ L_i = [\tau_i, \exp_{up,i}, \exp_{down,i}] \]  

for i=1, 2, 3, 4, ..., M

This implies that the i-th machine is capable of producing \[ c_i = \frac{1}{\tau_i} \text{ parts per unit time} \]

Uptime and downtime are distributed exponentially with parameters λ_i and μ_i, respectively.

The i-th machine is characterized by the triple:

\( (c_i, \lambda_i, \mu_i) \) for all for i=1, 2, 3, ..., M

The i-th buffer is characterized by its capacity N_i, i = 1, 2, 3, ..., M

Now these parameter can be used to represents the objective function for the machine provided the parameter is given by the machine vendor needed for modeling the machine in a production line for a specific product. The first Machine in the production line is foundation manufacturing machine. The objective function for this machine can be expressed as below:

\[ OBm_{-1}^{1 Beg} = \frac{\sum_{d=1}^{n} c_i e_i t_{cmax}}{\sum_{d=1}^{n} c_i e_i t_{cmax}} \text{ for } i = 1, 2, 3, 4, ..., \text{ upto } - n \] Equation-1
The following table represents the objective function for each machine corresponding to the operation on the product.

**Table 6** Individual Object Function for Each Machine in the Manufacturing Application

<table>
<thead>
<tr>
<th>No</th>
<th>Operation</th>
<th>Process</th>
<th>Notation</th>
<th>Object Function</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>Operation_1</td>
<td>Foundation</td>
<td>$OBm_{-1_{i}}^{Bcr}$</td>
<td>$\frac{3c_i}{c_{\text{max}}} \frac{1.5}{\lambda i} + \frac{1}{2\mu} \sum_{i=1}^{n} \frac{2.5, \text{ci, ei}}{c_{\text{max}}}$</td>
</tr>
<tr>
<td>02</td>
<td>Operation_2</td>
<td>Foundation</td>
<td>$OBm_{-2_{i}}^{Bcr}$</td>
<td>$\frac{c_i}{c_{\text{max}}} \frac{1}{\lambda i} + \frac{1.5}{2\mu} \sum_{i=1}^{n} \frac{\text{ci, ei}}{2c_{\text{max}}}$</td>
</tr>
<tr>
<td>03</td>
<td>Operation_3</td>
<td>Magnetic Core</td>
<td>$OBm_{-3_{i}}^{Bcr}$</td>
<td>$\frac{5c_i}{c_{\text{max}}} \frac{1.3}{\lambda i} + \frac{1}{2\mu} \sum_{i=1}^{n} \frac{\text{ci, ei}}{1.2c_{\text{max}}}$</td>
</tr>
<tr>
<td>04</td>
<td>Operation_4</td>
<td>Primary Coil</td>
<td>$OBm_{-4_{i}}^{Bcr}$</td>
<td>$\frac{3c_i}{c_{\text{max}}} \frac{1.8}{\lambda i} + \frac{1}{3\mu} \sum_{i=1}^{n} \frac{1.6\text{ci, ei}}{(c_{\text{max}} + 2)}$</td>
</tr>
<tr>
<td>05</td>
<td>Operation_5</td>
<td>Secondary Coil</td>
<td>$OBm_{-5_{i}}^{Bcr}$</td>
<td>$\frac{(c_i + \lambda)}{c_{\text{max}}} \frac{2}{\lambda i} + \frac{1}{\mu} \sum_{i=1}^{n} \frac{(\text{ci, ei} + 3Cx)}{c_{\text{max}}}$</td>
</tr>
<tr>
<td>06</td>
<td>Operation_6</td>
<td>Transformer</td>
<td>$OBm_{-6_{i}}^{Bcr}$</td>
<td>$\frac{(4c_i + 1.3\lambda)}{c_{\text{max}}} \frac{1}{\lambda i} + \frac{1}{3\mu} \sum_{i=1}^{n} \frac{\text{ci, ei}}{(c_{\text{max}} + 2)}$</td>
</tr>
<tr>
<td>07</td>
<td>Operation_7</td>
<td>Ignition</td>
<td>$OBm_{-7_{i}}^{Bcr}$</td>
<td>$\frac{c_i}{c_{\text{max}}} \frac{1}{\lambda i} + \frac{1}{\mu} \sum_{i=1}^{n} \frac{\text{ci, ei}}{c_{\text{max}}} \int c_{i}$</td>
</tr>
<tr>
<td>08</td>
<td>Operation_8</td>
<td>Integration</td>
<td>$OBm_{-8_{i}}^{Bcr}$</td>
<td>$\frac{c_i}{(\lambda i + 2)} \frac{1}{\mu i} + \frac{1.5}{\lambda} \sum_{i=1}^{n} \frac{\text{ci, ei}}{c_{\text{max}}}$</td>
</tr>
<tr>
<td>09</td>
<td>Operation_9</td>
<td>Assemble</td>
<td>$OBm_{-9_{i}}^{Bcr}$</td>
<td>$\frac{3(c_i)}{(c_{\text{max}} \cdot 2)} \frac{1}{\lambda i} + \frac{1}{\mu i} \sum_{i=1}^{n} \frac{\text{ci, ei}}{c_{\text{max}} \cdot \min c}$</td>
</tr>
<tr>
<td>10</td>
<td>Operation_10</td>
<td>Testing and</td>
<td>$OBm_{-10_{i}}^{Bcr}$</td>
<td>$\frac{1.5(c_i + \lambda)}{c_{\text{max}}} \frac{1}{\lambda i} + \frac{2\lambda}{\mu i} \sum_{i=1}^{n} \frac{\text{ci, ei}}{c_{\text{max}} \cdot \int 1_{i}}$</td>
</tr>
</tbody>
</table>
9.1. OVERALL OBJECTIVE FUNCTION

The overall objective function can be expressed as below:

\[ \text{OBJ}_{\text{OVERALL}} = \left( \frac{3\cdot e_{1} \cdot \frac{1.5}{\lambda}}{3\cdot \lambda + 3\cdot \mu} \right)^{i} + \left( \frac{2.5 \cdot e_{1} \cdot \frac{1.5}{\lambda}}{3\cdot \lambda + 3\cdot \mu} \right)^{i} + \left( \frac{5\cdot e_{1} \cdot \frac{1.5}{\lambda}}{3\cdot \lambda + 3\cdot \mu} \right)^{i} + \left( \frac{c_{1} \cdot e_{1} \cdot \frac{1.5}{\lambda}}{3\cdot \lambda + 3\cdot \mu} \right)^{i} + \left( \frac{1.5 \cdot c_{1} \cdot e_{1} \cdot \frac{1.5}{\lambda}}{3\cdot \lambda + 3\cdot \mu} \right)^{i} + \left( \frac{3\cdot c_{1} \cdot e_{1} \cdot \frac{1.5}{\lambda}}{3\cdot \lambda + 3\cdot \mu} \right)^{i} + \left( \frac{1.3\cdot c_{1} \cdot e_{1} \cdot \frac{1.5}{\lambda}}{3\cdot \lambda + 3\cdot \mu} \right)^{i} + \left( \frac{1.2\cdot c_{1} \cdot e_{1} \cdot \frac{1.5}{\lambda}}{3\cdot \lambda + 3\cdot \mu} \right)^{i} + \left( \frac{c_{1} \cdot e_{1} \cdot \frac{1.5}{\lambda}}{3\cdot \lambda + 3\cdot \mu} \right)^{i} \]

9.2. SIMULATION

The simulation of the mathematical model is carried in MATLAB 9.4- R2018a. The mathematical modeled equation which contains the parameter and variable is expressed in the above text. We have implemented GA on the equation defined so as to get the simulation plots. Then after execution, the optimization software has given different values for optimal combination. The Simulation plots are as listed below:

**Figure 6** Simulation Response Plot of Efficiency, Productivity & Performance with respect to suggested combination-1
Figure 7 Simulation Response Plot of Efficiency, Productivity & Performance with respect to suggested combination-2

10. RESULT AND CONCLUSION
There is a significant effect of the productivity of the manufacturing unit. The result are compared on basis on the following parameter, which are tabulated in comparison in the below text.

Table 7 Result Comparison

<table>
<thead>
<tr>
<th>No</th>
<th>Parameter</th>
<th>Old Combination</th>
<th>New Combination</th>
</tr>
</thead>
<tbody>
<tr>
<td>01</td>
<td>Efficiency</td>
<td>66%</td>
<td>74%</td>
</tr>
<tr>
<td>02</td>
<td>Production Time/Unit</td>
<td>60 Unit Time</td>
<td>40 Unit Time</td>
</tr>
<tr>
<td>03</td>
<td>Installation Cost</td>
<td>230 Unit Investment</td>
<td>216 Unit Investment</td>
</tr>
<tr>
<td>04</td>
<td>Stability</td>
<td>70%</td>
<td>76%</td>
</tr>
</tbody>
</table>

The result table-7 above concludes that Efficiency, Production Time/Unit, Installation Cost and Stability of the system has been significantly improved.

11. FUTURE SCOPE
Transient and unpredictable expectations in the dynamic cliental requirement; demands a optimal and flexible design of the floor for the unit of optimal design solution which still demands further research in the concerned field. The presented research can be extended to utilize designing the material flow, quality control, manpower management and to improve the overall performance of the search optimization technique. The work can be extended for delivery process. The work can be extended for effectiveness of stock rotation & Inventory Control. The work can be extended for handling storage, packing process and for monitored yearly physical stock verification.
REFERENCES


