A novel hybrid simulation – heuristic optimization model for production optimization with stochastic rework

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Abstract

One way to increase productivity is to increase throughputs without using more resources. In this paper, the issue of the optimal sequence of products in a job shop scheduling is raised, which has many uncertainties such as downtime, development time, etc. One of the key factors which affect operation time is the number of reworks. The number of reworks based on metallurgical parameters, the number of their operations according to defects count, and process time are quite probable. The innovation is in dealing with job-shop scheduling in which there are reworks in particular, and the addition of this parameter increases the complexity of JSSP. Therefore, this parameter is added to the mathematical model and with a combined method via the statistical method. The problem has been solved with simulation for meeting uncertain constraints and a heuristics approach for optimization. Implementing this model in a high-tech casting shop with a large number of different products reduces the Work in Process (WIP) and capital sleep, which reduces the number of parts in the queues. Also, decreasing the queue length in bottleneck has reduced the lead time and increased agility and, above all, increased the number of productions by about 3.3 percent.

Keywords

Heuristic optimization - hybrid Simulation -Rework- Bottleneck-Queuing systems- production optimization- multi-objective optimization

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Abbreviation

TOC: Theory of Constraint

WIP: Work in process

MPS: Master Production Schedule

DES: Discrete event simulation

SSPT: Short process probable time

NDT: Non-Distractive Test

CMM: Coordinate Measuring Machine

FPI: Fluorescent Penetration Inspection

RCCP: Rough Cut Capacity Planning

COFC: Certificate OF Conformity

1. Introduction

One of the main objectives of every company is to improve production efficiency. To increase productivity and reduce operating costs of the production line, optimizing production sequence among workstations is performed. They can be done by different methods, such as exact algorithms, heuristics, meta-heuristics methods, simulation, etc. [1]. Increasing the number of workforces, extending time durations of the shifts, application of new technologies and machinery and many other possible approaches can enhance the production throughout [2]; however, the focus of industrial engineering is to avoid the additional costs which may come along. There are always many limitations that prevent the optimal production of processes in terms of number. One of these constraints is the bottleneck [2]. It directly affects the output and the production rate in a manufacturing system. A bottleneck can causes the overstock of Work in process (WIP), an unbalanced flow of components, and in some cases the extremely slow operations (when some of the stations are overworked and a number of them are idle) [3]. According to the Theory of Constraint (TOC), the efficient use of resources in manufacturing systems is limited by the capacity of the bottleneck resource [4]. Therefore, we in this article focus on bottlenecks to maximize production by optimally combining the annual plan. The theory of this paper is based on four techniques. First, SPT (short process time) technique, which was compared between 4 rules, the results showed that the SPT (shortest processing time) machine scheduling rule was better than the other method [5], and from then until it is now used as one of the planning techniques in assigning work to the machine. The second technique is EDD (Earliest Due Date), used for the problem of scheduling which simultaneously jobs (with known means), on a single machine, for minimizing the mean delay [6] and is based on faster delivery of parts to the customers. The third technique that emerged from the development of the Solberg model was the Me-jabi model, which specifies the WIP standards [7]. The last technique is the mathematical expectation in statistics, which is used to estimate the amount of a possible variable. Our problem is a JSS (Job Shop Scheduling) with backward conditions and has limitations including probable operating time, various downtime such as machine failure and inventory shortages, as well as NPD (New Development process) that have uncertainties. In addition to process uncertainties, sales plans are also divided into two categories, one according to the customer's order should be sent on time and the second category according to forecast should be delivered to the warehouse. So, to solve this scheduling problem, one needs to combine the mentioned techniques to have the maximum production number with the minimum amount of WIP and also deliver special orders to customers on time.

As far as I know, in the review literature, various combinations between heuristic and simulation methods have been created to be used in solving dynamic scheduling problems, but in these researches, the assumption of reworking time has not been considered as an effective parameter. However, in some high-tech industries such as casting turbine blades, where the high-level quality, the amount of rework due to non-conformity is high in the workshops and takes plenty of time in the process. And if this important factor is not taken into account in the calculations, the resulting outputs will not correspond to reality and cannot be properly optimized. In this paper, a creative method has been applied in the allocation method (multiple tasks to a machine) called Short Process Probable Time (SPPT) to add the probable rework time in the model Then all the limitations are considered in the simulation software and according to the output in Excel software, with the help of coding, a better sequence is created each time so by repeating this method JSSP, which is NP-Hard, achieves optimal response in a very short time compared to other metaheuristic algorithms. The result of this method is optimization by considering possible rework times and obtaining the result in much less time than the other algorithm similar to the genetic algorithm (GA). The rest of the paper is organized as follows. The next section presents a literature review sort by date. The methodology will be outlined in the third section. In the next part, analyses of a case study are explained. Verifications and validations are written in section five and as usual conclusion and reference are coming at the end of the essay as part six and seven.

2. Literature review

2.1: Heuristic methods

Accurate algorithms are used only for small problems, so heuristic and meta-heuristic algorithms are used to solve more complex problems. For a complex job shop scheduling, probably random dispatch rules are the best way to solve planning problems [8].[9] to solve the VRP (vehicle routing problem with multiple trips) used multi-phase constructive heuristic and minimize, the maximum amount of overtimes. The results obtained, compare with similar topics in the literature and showed the efficiency of the model. In the other research the genetic algorithm used for solving a multi-attribute combinatorial dispatching (MACD) decision problem in a flow shop with multiple processors (FSMP) environment. They created a method for GA parameters to optimum time of performance. Implementation of this method achieved a 28% improvement. Due to minimizing the fuzzy makespan hybrid artificial bee colony (HABC) algorithm was employed and best parameter values are suggested by design of experiment (Based on the Taguchi method) then with numerical testing results and compare with some existing algorithms, effectiveness of the proposed HSBC were approved [10]. [11] For the university course timetabling problem, a heuristic algorithm was used. Due to operations and steps were random or probable, it is not possible to provide one timetable, so the best solution was chosen among the generated ones with a special index such as minimizing the class replacements for the teachers and their presence in the university to generate a timetable with the best performance. [12] For optimizing production rate, three objectives were met. Planning was done in a probable environment and some uncertain parameters were considered for the problem. The simulation-optimization method applied and a heuristic algorithm was used for optimization. After generating 225 repeats, the optimal production rate was determined. Results showed that 75% improvement was created. A mathematical model for allocating AVGs was employed to handle scheduling and allocating AVGs in the process which was include allocating, navigating, and timing then with a heuristic algorithm solved model to minimum makespan [13]. New research creates an effective backtracking search based hyper-heuristic (BS-HH) approach to solve the FJSPF. In this study for constructing a set of low-level heuristics, six simple and efficient heuristics were used for the BS-HH then a backtracking search algorithm was showed as the high-level strategy to manage the low-level heuristics for operating on the solution [14].

2.2: Simulation

In the Fundamentals of Queueing Theory book, papers related to scheduling problems were provided by [15] then [16] for improving the missed due date performance in dynamic, stochastic, multi machine job shop environments, mean absolute lateness (MAL) and mean square lateness (MSL) has been considered as a performance criterion then a new due date assignment model and dynamic dispatching rule in simulation environment was developed. The results showed that this method was very successful for improving the missed due date performance. [17] their study shows that simulation-based optimization is used for analytical optimization. They believe that simulation optimization technology can enhance intelligent decision-making and analyze a complex system more easily than traditional optimization methods. The research path focuses on a simulation-based experimental study of the interaction between due-date assignment methods and scheduling rules in a typical dynamic job shop production system. In order to implement, four due-date assignment methods and seven scheduling rules were compared. In this study, it was found that all these methods can be extracted in simulation analysis. [18] They had predicted that simulation modeling to be able to represent real-world complex systems and constraints. They think simulation-based optimization approaches are derived from dispatching rule-based approaches. They presented an SBO system integrated with the shop floor database system. This method used real-time data from the production line and sent back expert suggestions directly to the operators through the Intermediary file then generated new MPS and enabled the users to easily monitor the production line through visualization and allow them to forecast target performance measures. The results have shown that such a novel scheduling system can help both in improving the line throughput efficiently. [19] simulation methods were used for optimization with solving NP and NP-hard problems. It is combined with heuristics methods to solve job shop scheduling with plenty of constraints. They developed evolutionary simulation-based heuristics to construct near-optimal solutions for dispatching rule allocation. Their heuristic method was easily used and gave a manager a useful tool for testing a configuration that can minimize certain performance measures. [20] had suggested dependency structure matrix (DSM) to tackle constraints like uncertain operation time, information flow, and routings, and simulation was used for optimizing project duration. In this model, Firstly, inputs were generated based on the probability distribution random numbers. Then, minimized project duration by using the DSM method and Monte-Carlo simulation; when the simulation turns stable, durations were achieved. [21] For reducing the average waiting times of the trucks. This study begins with timing the docks and different stations to access the system's factors. To simulate the system, ARENA 14 software was used then after validating the proposed model and confirming its validation, scenarios would be made in order to remove the bottlenecks. Finally, some scenarios that decrease the trucks' wait time significantly were compared and prioritize among the most economical solutions would be presented. The aim of other study was to determine the max production rate and min time of period for preventive maintenance in an FPMS for this problem, discrete event simulation was used [22]. (Sajadi, Ghasemi, et al. 2016) All possible solutions were considered and their cost was calculated, then the most economical method among them was introduced as the best method then to synchronize and control machine production they developed a new method combining the theory of optimal stochastic control, discrete event simulation, test design, and the Automated Response Surface (RSM) method. In this method, it is also possible to check the failure rate based on the age of the equipment, maintenance policies, especially preventive maintenance policy. A heuristic algorithm combine with simulation was proposed to solve the scheduling and allocating AVGs in the manufacturing process of a specific project [23]. For planning and managing new product development projects that are uncertain in terms of the type of activities, time, and resources, the use of simulation is an advantage because there is no need to design accurate mathematical modeling and can be used as a conceptual model. The simulation takes into account all stochastic constraints and can easily provide capacity assessment, time balance of activities, and an advanced production program (MPS). In another study, the strategic role of simulation is discussed and the continuous improvement in technical and tactical fields that can be created by this tool is mentioned [24]. Using simulation to improve productivity in comparison to the traditional conditions in one of the automotive premises in Pahang, Malaysia. To improve the performance of production activities two new alternatives layouts were proposed and analyzed by using Witness simulation software. This method showed a valuable and better understanding of production effectiveness by adjusting the line balancing. The simulation was used for comparing and improving efficiency and productivity. The proposed design plan has shown an increase in yield and productivity compared to the current arrangement [25]. To minimize production costs according to demand, simulation tools were used and a model for simultaneous optimization of production line scheduling has been prepared. In this model, production costs are also addressed to maximize savings in this field [26]. [27] the main objectives of the other essay were to balance the trade-off between the cost of logistics and customer' experience by using simulation. The models were made by [28] , can realistically show the flow of materials in the factory, and this simulation model can be used to create new approaches and increase Technology Readiness Level (TRL).

2.3: Job-shop scheduling

Swarm optimization (PSO) was used for multi-objective job-shop scheduling problems. The authors modified the motion, velocity, and position of the particles for use in the model [29, 30]. To reduce the delivery time of the product in the case of flexible job-shop scheduling, the startup time variable has been added to the model. Also, random breakdowns have been included in the model and the aim was to reduce the average inventory and delay cost [31]. A new hybrid genetic algorithm and simulated annealing (NHGASA) algorithm was used to solve the multi-objective flexible job-shop scheduling problem (FJSP) this method decreases computation time and extremely increases the quality of the solutions for multi-objective FJSP. the results show that the multi-objective results of the NHGASA algorithm overcome other approaches for solving the FJSP [32]. [2] for minimizing the cycle time in a plan, they used neural networks. This model introduced a fascinating model for manufacturing production, and it was also very productive, and flexible to work with the previous method. The league championship algorithm (LCA) had to modify to work for discrete scheduling problems. For this sake, (Sajadi, Kashan et al. 2014) let LCA searches within the continuous space, but do evaluations in a discrete space via a heuristic rule to make a relation between the continuous and discrete spaces. Results of LCA applied to well-known benchmark suites were presented and compared to the well-known approaches such as genetic algorithm, particle swarm optimization and differential evolution algorithms. On the adopted benchmark suite, LCA had a better result. In another study, three-step was presented: First, the use of IoT technology used for the scheduling problem. In an IoT-enabled manufacturing workshop, production resources can interact with each other, and resources are controlled. The second method was developed to increase production efficiency and reduce environmental pollution using the MPPRS method. The third method was to optimize the game for MPPRS and was used to assign operations to the machines. For the first time, the GRASP / G & T algorithm was used to solve FJSP and DFJSP with constraints such as changes in delivery time, cancellation of orders, and the like. Decisions that reduce the problem of resource adjustment were also considered to better reflect timing factors in real production environments. Strong and sustained planning for a flexible job problem with probable machine breakdown was discussed by [33].

To generate a predictive plan, a two-stage genetic algorithm was investigated. The first step optimizes the main target, which minimizes delivery time when the data was stable and there was no downtime. The second stage pursues two goals, which included due-date and system stability, in which the system had random failures. For this stage also a simulator model created for machine failure [34]. To minimize makespan, the lexicographic method was used in DFJSP for four objectives. In the first step, GRASP was utilized for solving three groups of benchmarks from the literature in static FJSP then are compared with the best-known algorithms. At second step the performance of the GRASP and periodical rescheduling policy were compared with each other and with basic logistics rules over differing levels of the rescheduling time interval, machine flexibility, shop utilization, and due date tightness. To conclude the periodical rescheduling strategy was better than schedules with the other methods. Digital twin (DT) in five-dimension for a machine in the job-shop environment was introduced by [35] then the DT-based machine used for prediction, the mess, and Key Performance Indicators (KPIs). Based on this, a DT-enhanced dynamic scheduling methodology was introduced [36]. Optimized risks both in performance and stability for the job shop scheduling with random machine failure, in which makespan, makespan risk, and stability risk were addressed at the same time. A variable neighborhoods search (VNS) algorithm was developed to solve JIT-JSS. This algorithm determines the completion time by dividing the problem into smaller components and obtaining local optimizations, and uses developed variable neighborhoods search (VNS) algorithm. [37].

Table 1 gives an overview for literature above. It is noted that the main study in each field. The first column is field, the second is author, the third is the method used, and the problem which is considered is in the last. It should be noted that since this article uses numerical methods, the literature review has been limited to heuristic and probabilistic methods.

3. problem statement

In the job shop environment, queues should be minimal at stations to ensure minimum WIP, according to the Mejabi model (Me-jabi 1989), and the maximum number of outputs. In today's competitive manufacturing world, changing the production schedule due to changes in sales sequence is inevitable. The subject of this research is based on the problem that exists in the sequence of sales orders received and a large number of reworks in one of the high-tech factories making turbine blades for gas turbines. A different sequence of the orders changes the queue at different stations so the bottleneck changes, for example, **Fig.1** show the different effect on operation production in some stations with the deferent sequence (numbers are based on real statistics from previous years). With each change of the sales order, by optimizing the production schedule sequence, the maximum number of outputs should be created (some products have a special due date) in which many probable parameters such as failures, lack of raw materials, and particularly a large number of reworks that consume a plenty amount of time should be considered. Since changes occur constantly in sales programs, the execution time of the model is also very important.

The following assumptions are used in this research:

- All machines and jobs are “on” status at starting;
- For each machine we have only one job at a time;
- One operation of a job can be done if the preceding is satisfied;
- Sales orders are not probable and will be delivered at the requested time
- scheduling strategy is based on both MTO and MTS

4. Methodology

The problem of planning in complex production systems involves complex combination problems that are not easy (or maybe not possible) to solve with analytical approaches in an acceptable time (see model No.1). So, in this paper for analyzing the production line, non-discrete event simulation was used with all constraints like machinery capacity, scrap rates, nonconformity and rework parts, the number of machines, and also technical constraints such as components batches, heat treatment cycles … to obtain outputs and analyze the bottleneck utilizing average waiting time and the average number waiting. The next step heuristic model is applied for using SPPT include rework time to maximize line output.

SPT was used to minimize the average job duration for jobs performed on a machine but rework times was non-exact (probable). So, short process probable time (SPPT) was a new method, which adds to the model to giving priority to the job with the least operation duration.

For optimum dynamic scheduling in the job shop production line following model should be solved:

Notations used for model:

I: Number of products,

S: Number of stations,

J: Number of months, (planning scope)

AT_s: Available Time for station s and s= [1… S]

Mij: Minimum requirement of product i in month j asked by the customer,

Ni: Sum of product i in year (or planning scope),

QL_s: Queue length for station s,

Xij: Optimal number per month and per product,

$StWIP_s$: Standard WIP in Station s,

The model that should be solved for optimizing the production output is as follow:

- **model (No.1):**

$$\min(QL)_s,\quad \sum_{i=1}^{I}\sum_{j=1}^{J} X_{ij} \tag{1}$$

St:

$$QL_s \geq StWIP_s \tag{2}$$

$$\sum_{i=1}^{I} ST_i * X_{ij} \leq AT_S \qquad \text{for s } \epsilon \text{ [1, 2... S], j } \epsilon \text{ [1, ..., J]} \tag{3}$$

$$X_{ij} \geq M_{ij} \qquad \text{for i } \epsilon \text{ [1, 2... s], j } \epsilon \text{ [1... e]} \tag{4}$$

$$\sum_{j=1}^{J} M_{ij} \leq \sum_{j=1}^{J} X_{ij} \leq \sum_{j=1}^{J} M_{ij} \qquad \text{for i } \epsilon \text{ [1, 2... s]} \tag{5}$$

$$X_{ij} \geq 0,\ QL_s \geq 0 \tag{6}$$

$$StWIP_s = \frac{A * U * PC * MLT}{Shift * Hours} \tag{7}$$

This model was NP-hard type and cannot be solved with existing software. So, the solution according to the previous explanations is as follow:

Notations used for this kind of scheduling rules:

B: represents the set of jobs performed before *i* and *j*,

A: represent the set of jobs performed after *i* and *j*,

i: index of the job for which the priority values are calculated,

j: index of the operation of job j,

tx: time of job *x*,

E(Trex): the mathematical expectation of job x rework time,

F_k (S): Stands for the flow time of *Kth* job in sequence *S*,

First: The use of the probable time and the probable number of reworks: Given the high number of parts produced per year and the amount of rework, it can be assumed (according to the rules of statistics) that rework time follows the normal distribution function with (μ, δ). And the frequency of repetition of these reversals is also a probable function that increases the complexity and time of calculations in the model, so to solve this issue, the mathematical expectation has been used to achieve the optimal result:

Notations

n: Number of reworks (product per station),

$T_{re:}$ Time of rework (product per station),

T: Time of operation

t_i: Standard time

$$n \sim N(\mu_1, \sigma_1), T_{re} \sim N(\mu_2, \sigma_2) \tag{8}$$

$$T = t_i + n * T_{re} \tag{9}$$

Supposed:

$$t' = T_{re} \quad \text{so} \quad T = t_i + t' \tag{10}$$

And

$$t' \sim N(\mu_3, \sigma_3) \tag{11}$$

As result:

$$T = t_i + E\left(N\left(\mu_3, \sigma_3\right)\right) \tag{12}$$

And

$$T = t_i + \mu_3 \tag{13}$$

- According to the above relations, the operation time is a combination of the operation time and the probable rework time, which will be calculated according to Equation (13) in the continuation of the article.
- Second, we prove SPPT decreasing the average duration of work in *N* work to 1 machine:
- Assumed:

$$t_1 \leq t_2 \leq \ldots \leq t_n \tag{14}$$

On the other hand:

If one member of each system becomes probable, the whole system will become probable, so the mathematical expectation is used in term of probable time:

$$t_i = t_i + E\left(T_{rei}\right), t_i = t_j + E\left(T_{rej}\right) \tag{15}$$

In a sequence supposed: ***ti* < *tj*** for simplicity of calculations:

$$t_i = n, t_j = 2n \tag{16}$$

$$\sum_{k=1}^{n} F_k(S) = \sum_{k \in B} F_k(S) + F_i(S) + \sum_{k \in A} F_k(S) \tag{17}$$

In order to compare two sequence modes, $\sum_{k \in B} F_k\ (S)$ and $\sum_{k \in A} F_k\ (S)$ are considered constant. So,

Sequence 1: first priority t_i

$$\sum_{k=1}^{n} F_k(S) = t_i + t_j \tag{18}$$

With Placement:

$$\sum_{k=1}^{n} F_k(S) = n + (2n + n) = 4n \tag{19}$$

Sequence 2: first priority t_j

$$\sum_{k=1}^{n} F_k(S') = t_j + t_i \tag{20}$$

With Placement:

$$\sum_{k=1}^{n} F_k(S') = 2n + (2n + n) = 5n \tag{21}$$

As result:

$$\sum_{k=1}^{n} F_k(S) < \sum_{k=1}^{n} F_k(S') \tag{22}$$

Therefore, it can be concluded that in the operation sequence, if the total operation time and rework time were smaller, it should be given less priority until the workflow time was reduced. This method is used in the following heuristic method.

***Third:* Heuristic model:**

Notations used for heuristic model:

Q_i: Queue length of Station *i*
X_j:Total output after *jth* improvement
A: Queue length of longest queue
n: Station's index
H: Homogeneous coefficient
A: Availability of work center
U: Productivity
PC: Product capacity
MLT: Mean lead time

In meta-heuristic models, an initial model is built and then trying to improve the solution. The algorithm created in this paper is like the genetic algorithm, but with the difference that the use of allocation methods and the Mejabi model (Me-jabi 1989) (for WIP) in the production lines of the workshop results in a very short time due to the reduction in the number of iterations. Model is described as below and **Fig.2**:

1 :The number of parts in the queue, obtained from the simulation, was used as the model input

$$\max(QL_1, QL_2, ...QL_s) \tag{23}$$

2: In the next step, based on the station(n) that was included in the model in the previous paragraph, the time of parts operation that caused this bottleneck were determined.

$$\text{Time of bottleneck station} = \sum_{i=1}^{I} ST_i * X_{ij} \tag{24}$$

3: Modification is performed on the annual schedule using the SPPT method as follow (see transfer code in appendix):

1- The product with less time, remain in *Xij* and the product with more time are moved to the next month

2- Equivalent (using Homogeneous coefficient (H)) are replaced by parts with less time

3- This work continues so that all parts reach the customer's minimum requirement.

- If the products that have created the bottleneck interfered with the previous bottleneck, the total time of both operations per product would be the criterion for performing SPPT

4: Check stop condition as follow:

- Given that the production program can be a combination of two production plan (MTS, MTO), each product in each *Xij* can be moved by SPPT method unless there was a time limit by the customer. In this case, up to the minimum customer needs can be moved (according to EDD strategy). Therefore, ***the first condition*** was that all products (*Xij*) have reached the minimum requirement level.
- ***The second condition*** was that the number of parts in the queue in the bottleneck station, which was derived from the simulation, be equal to the standard number of WIP (Me-jabi 1989) which calculate as below

$$WIP = \left(\frac{A * U * PC * MLT}{Shift * Hours} \right) \tag{25}$$

5: MPS was transferred to the simulation to continue the cycle.

• Due to in each cycle all stations were investigated, this algorithm did not fall into a local optimum trap.

As mentioned above, the flowchart below shows how to do the whole procedure:

5. Experimental study and results

The mentioned method was tested in one of the factories of MAPNA Group in the casting shop. In this shop, parts with high technology were produced. The production process in the casting shop is shown in **Fig.3** consists of 3 shops (Pre-Cast Shop, Post Cast Shop, and Non-destructive Testing (NDT) Shop) and 13 Station, the average operation in each Station was 5. So, we had 65 operations in these shops which described as follow:

Wax models were built based on the production plans. This workshop includes shaping wax models, controlling their quality, leveling surfaces, and changes them into clusters (1). In Shell Maker clusters were covered by a layer of ceramics this workshop is created for layering and creating a ceramic model and prepares the mold for melting (2). These ceramics shells were transferred to the casting shop (4) where wax models were removed in these stations and melting was done and blades were cut, separated and the extra parts were sent to the waste section. Cores (if used) were eliminated and leached, of course, some of them need reworks here. They would stay in this part for a long time to do this process (5). Parts transferred to the clean unit were surface clean by handwork. In this part, all the blades were prepared for heat treatments (6). In Heat treatment workshops, the operations required for reshaping are performed with special cycles according to their materials. Non-destructive Testing (NDT) with special inspection procedures were defined and carried out for examining the imperfections of components (9, 10, 11). NDTs were followed by a final visual inspection where the latest technical and visual inspections were performed and the parts were ready to be delivered to the customer (12). The warehouse is created for the temporary storage of goods and the parts are kept in this place until they are received by the customer.

5.1: Running the solution

- MPS was created by the sales department, then a comparison between available and required resources for months using Capacity Requirement Plan (CRP). This comparison suggests insufficiency in the capacity of some stations in some periods. Based on the gathered information, a simulation model was built by using Arena software which illustrated the structure and conditions of our current state. To reduce the volume of data, only 8 stations with the longest queue were represented in the article. Also, the 1 to 5 and last run to show the final result are displayed. Time for these runs with P7-Core i5 and 8G Ram take 4 hours. **Table 2** is the result of the First run. Reports affirmed that Core Leach had the biggest bottleneck.

- In this step, the heuristic model was used. The first improvement was used to optimize the core leach station and rearrange MPS then repeat the cycle which results were shown in Tables 3 to 7.

Table 3 presents the results of the first improvement and shows the optimal result in the first bottleneck (Core leach).

A comparison of improvements three and four are presented in **Table 4**, stations Clean, FPI, and CMM have been optimized in these two phases and a favorable result has been created in the number of production outputs. The fourth performance showed that the third performance was optimally local. But in the next round the results were better and showed that the local optimization does not stop the algorithm.

In runs 5 and 6, the algorithm is repeated and moves to the last stations, due to there is no noticeable change in the number of queues, the change in the output value is not noticeable (see **Table 5**).

Runs seven and eight, like the previous two performances, made small changes to the output which presented in **Table 6**.

The last run was performed in the last stations and create the last change in the outputs, which can be seen in **Table 7**.

Outputs were shown in **Fig.4**. After 10 run (last run) all X_{ij} achieve to minimum requirement or ST WIP. This means that the maximum number that can be removed from the production line with the combination is 10 repetitions.

Fig.5 shows the reduced number of WIP. In runs, it has sometimes decreased due to travel of the bottlenecks, but in the end a planty amount of WIP has been reduced, which is about 26% of the total WIP.

6. Verifications and validations

To carry out verifications, we used tracing as follows: To identifying the bottlenecks, the RCCP file and field observations were used as verification tools for the recognition of bottlenecks. The outputs of Arena were confirmed by the results of RCCP. Besides, production line observations, which can also be acquired by SAP (ERP system), proved Wax CMM, FPI Defect Removal, Core leach, and Finishing CMM to be the bottlenecks. Actual outputs and collected data (from the software) had a deviation of about 8% in a one-year comparison, which was negligible due to the existing constraints (about 80 products in 55 operations with at least three-month LT).

For the validation model analyzing the results of improvements with the statistical method was used. To check the new MPS, created with our solution, this plan was run for one year and results, which data shows in **Table 8**, compared with the last period in 12 months, and data were analyzed by Analysis of Variance (ANOVA) in Minitab, shown in **Table 9** and Fig.6. P-value shows that H0 was accepted because there was no big difference between base plans, receive from sales unit, solution plane, and actual. In the second step, the new MPS was analyzed by experts who have worked in the production plane unit (expert system), and they accept this change to pass the needs of the customers.

μ_{AO}: (μ $_{\text{Actual Output}}$): Actual number produced in twelve months
μ_{MO}: (μ $_{\text{Model Output}}$): Number produced in twelve months by the model introduced
μ_{SN}: Number requested in twelve months by the sales unit

So:

H0: $\mu_{OA} = \mu_{MO} = \mu_{SN}$
H1: $\mu_{OA} \neq \mu_{MO} \neq \mu_{SN}$

The data collection method for **Table 8** is as follows:
The sales plan data is sent by email to the planning unit, the output data is collected from the simulation software in Excel, and the actual data is extracted from the SAP system, which is the factory integrated software.

Table for ANOVA, run in Minitab, for data is as below:

Normal probability plot shows the relationship between the theoretical and sample percentiles is linear and a few points lying away from the line implies a distribution with outliers. As can be seen in **Fig.6**, the production, order and sales order to be very close to predict and indicate the correct operation of the model in optimizing and meeting customer needs.

7. Conclusion

In this research due to the special method of sales orders, which in some orders with the MTO policy and in some of them with the MTS method, a combination of the SPT (with Probable time) and EDD methods were considered in the optimization model and for reducing the amount of WIP in the line production Mr. Me-jabi model was used and acceptable results were obtained, which can be seen in **Fig.4** and **5**. The simulation is used to create a model and heuristic methods to optimize scheduling. In which the probable rework time adds to the model to complete the previous models in this literature. The main objective of this work could be summarized: Initially, the proposed method was used to obtain the operation time of each part according to the probable rework time, then the production method was modeled in the simulation software, the bottlenecks were determined and the heuristic method with using SPPT and EDD allocation methods was used and the annual program was re-arranged to reach the maximum output and the execution time of the optimization model was about 4 hours, which was a very good time. This method was experienced in a high-tech production line and the results of one year are registered. Data showed an increase in output with almost 80% accuracy, it has reduced the amount of production procurement time in some parts (due to the reduction of the waiting time of parts in bottleneck stations) and has increased agility in responding to the customer due to increased accuracy and creating priority in bottleneck stations. The percentage of deviation was related to a malfunction in supplying raw materials due largely to sanctions which cannot predictable with the last data. Therefore, these findings could be exploited by factories with a job-shop production system and lead to production optimization especially with the probable time of the rework.

For extend of this research: First how to consider stochastic sales order in this model which causes increased complexity in rearranging MPS. Second, from the data available in recent years, the impact of sanctions on the supply of raw materials should be considered and added to the simulation model. For further future work, we decided to study the effect of FMS on the injection dies because of the significant impact on the rate of reworks. In order to reduce the variation of the rework rate, which causes time deviation, calculation of the amount of stability and process capability and its impact on this issue should be done to move closer to model real-life dynamic scheduling problems.

8. Appendix

Bellow code was written according to Visual Basic. It can be used with different database-like access, excel, etc. So, the parameters should sync with the database. For example, in excel M11 should swap with sheet1.cells (2, 3). For more clarifying Table 10 is represented.

ALGORITHM 1: Iterative Algorithm

Private Sub Form Click()

```
Dim y, i, R1, j, max (t), min (t), R2, D, u, temp_o, temp_i, w, o, A, p as integer
For y=1 to q-1
 Max (t) =0, R_1=1
 For i=1 to j                        'Get the longest operation time (based on bottleneck station time)
     If M_ti > max (t) and M_Si =0 then
        Max (t) = M_ti
       R_1=i
     End if
 Next i
 M_SR1=" forwarded"
 Min (t) =120                        'Longest operation time
 For i=1 to j                        'Get the shortest operation time (based on bottleneck station time)
     If M_ti < min (t) and Ms_i=0 then
        Min (t) = M_ti
       R_2=i
     End if
 Next i
```

```
p=0                                    'transferring product with maximum time to next month
 For o=1 to j
     If StatuMoR1<1 and p=0 then
        M (o+1) R1 = M (o+1) R1 + MoR1
        StatuMoR1=1, StatuM (o+1) R1 =1, p=1
        Tempo =Round down (MoR1*HR1)
        MoR1=0, s=o
     End if
 Next o
    D=0                                 'Transfer the product with the shortest time to the desired month with the reduced product size in the previous section
    Tempi=0
  p=0
 For o=2 to j
     If StatusMoR2=0 and p=0 then
         A=o, p=1
     End if
 Next o

       For u=1 to j
            If tepmi < tempo then
                 For w=1 to MAR2
                      If (w*HR2) < (tempo-tempi) then
                           D=w
                      End if
                 Next w
               MAR2= MAR2 – D, status MAR2=1
               MsR2= MsR2+D, status MsR2=1

                  If M AR2= MjR2 then
                     MsR2=" reduced finished"
                  End if
               A=A+1
             Tempi=roundup (D*HR2+ tempi)
            End if
       Next u
Next y
End sub
```

9. References

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Figure and table captions:

Table 1: Overview for literature

Table 2: First run: Simulation outputs, which shows the number of parts in the queue and the amount of waiting time at the main stations

Table 3: Comparison of simulation output results after the first and second execution and the rate of WIP reduction in Core leach station

Table 4: Comparison of simulation output results after the third and fourth execution and the rate of WIP reduction in Clean, FPI, and CMM stations and increase in outputs

Table 5: Results of the fifth and sixth runs that did not created significant change in the output

Table 6: Runs seven and eight with small changes have slightly increased the output

Table 7: The last run and the optimal amount show the number of parts in the queue as well as the maximum output

Table 8: Three field data for validation

Table 9: Analysis of Variance (ANOVA)

Table 10: Plan format

Fig.1: Average number waiting (Y-axis) due to different sequences in some stations (X-axis), which indicates the effect of product program sequence on stations and production queue balance

Fig.2 The research method

Fig.3 Flow Process Diagram

Fig.4 With the implementation of the algorithm, the amount of increase of outputs, which is the main purpose of the article, is showed. it starts from the first execution (zero value) which is the basis of the improvement and ends with execution 10 which is the end of the algorithm.

Fig.5 With the implementation of the algorithm, the amount of decrease WIP is showed. it starts from the first execution (zero value) which is the basis of the improvement and ends with execution 10 which is the end of the algorithm.

Fig.6 residual chart which showed that the production, order and sales order to be very close to predict and indicate the correct operation of the model in optimizing and meeting customer needs.

Figure and tables:

Table 1: Overview for literature

Row	Author	Scheduling Problem			Probable state		Failure status		Maintenance strategy			No. of Product type		Backward/forward process		Research method				Objective function		
		Job shop	**Flow shop**	**Network**	**Stochastic**	**Deterministic**	**Failure prone**	**No breakdown**	**No maintenance**	**CM***	**PM****	**Mono product**	**Multi product**	**Rework**	**No back ward**	**Simulation base**	**Fuzzy**	**Heuristic**	**System dynamic**	**Makespan**	**WIP**	**Cost**
1	Tavakoli, M.M., et al. 2018	√				√		√	√				√		√			√		√		
2	Petch and Salhi 2003			√		√		√	√				√		√				√	√		
3	Kaviani, Shirouyehzad et al. 2014			√	√			√			√		√		√			√		√		
4	Aiassi, Sajadi et al. 2020			√	√			√			√	√			√	√						√
5	Sadegh, Seyed Mojtaba et al. 2018			√		√		√	√			√			√	√						√
6	Mohammadi, Sajadi et al. 2014			√	√			√		√		√			√	√				√		
7	Vinod and Sridharan 2011	√			√			√		√			√		√				√	√		
8	Korytkowski, Wiśniewski et al. 2013	√			√			√		√			√		√	√						√
9	Sajadi, Ghasemi et al. 2016		√		√			√		√		√			√	√					√	
10	Baykasoğlu, Madenoğlu et al. 2020	√			√		√				√	√			√				√	√		
11	Tao and Xu-ping 2018	√			√		√			√			√		√			√		√		
12	Wang, Yang et al. 2020	√				√		√	√				√		√			√				√

13	Bagheri and Zandieh 2011	√				√		√	√		√		√			√		√
14	Shahsavari-Pour and Ghasemishabankareh 2013	√			√			√		√	√		√			√		√
15	Ahmadian, Salehipour et al. 2021	√				√		√	√		√		√			√		√
16	Jian Lin, 2019	√			√			√		√	√		√		√			√
17	Zhang, Tao et al. 2020	√			√			√		√	√		√				√	√
18	Wang, Zhou et al. 2013	√			√		√			√	√		√		√			√
19	Kechadi, Low et al. 2013	√			√			√	√		√		√		√			√
20	Yang, Kuo et al. 2007		√		√		√			√	√		√	√				√
21	Lugaresi, Alba et al. 2021			√	√		√		√		√		√	√				√
This article	Salehi, Sajadi et al. 2020	√			√		√			√	√	√				√		√

CM*: Corrective maintenance is a maintenance task should be done to identify, isolate, and rectify a defect so that the breakdown equipment, machine, or system can be repair to an operational condition within the tolerances or limits established for in-service operations.

PM**: Preventive maintenance (or preventative maintenance) is maintenance that is usually performed on a equipment to lessen the probability of it failing.

In the rest of this essay, we will consider the rework as an effective parameter, shorter execution time and maximizing outputs while minimizing WIP.

Table 2: First run: Simulation outputs, which shows the number of parts in the queue and the amount of waiting time at the main stations

Row	Work station	Average Number Waiting (pc)	Average Time Waiting (day)	Average WIP	Outputs
1	Wax CMM	48	0.7	B	A
2	VIMs	150	3		
3	***Core Leach***	**732**	**21**		
4	cleaning	180	5		
5	FPI Defect Removal	227	5		
6	Finishing CMM	421	8		
7	RT	108	3		
8	Final inspection	80	2		

Table 3: Comparison of simulation output results after the first and second execution and the rate of WIP reduction in Core leach station

Row	Work station	First Run				Second Run			
		Average Number Waiting (pc)	Average Time Waiting (day)	Average WIP	Outputs	Average Number Waiting (pc)	Average Time Waiting (day)	Average WIP	Outputs
z1	Wax CMM	48	0.7	B	A	46	0.8	B-180	A+8
2	VIMs	150	3			165	3.5		
3	*Core Leach*	732	21			345	12		
4	Cleaning	180	5			342	8		
5	FPI Defect Removal	227	5			211	5		
6	Finishing CMM	421	8			563	12		
7	Radiography Test	108	3			110	3		
8	Final inspection	80	2			72	1.9		

Table 4: Comparison of simulation output results after the third and fourth execution and the rate of WIP reduction in Clean, FPI, and CMM stations and increase in outputs

Row	Work station	Third Run				Fourth Run			
		Average Number Waiting (pc)	Average Time Waiting (day)	Average WIP	Outputs	Average Number Waiting (pc)	Average Time Waiting (day)	Average WIP	Outputs
1	Wax CMM	70	1	B-631	A+445	72	1	B-590	A+405
2	VIMs	155	3.5			157	2.9		
3	*Core Leach*	295	9			295	9		
4	Cleaning	205	5.3			140	3		
5	FPI Defect Removal	208	5			160	3.5		
6	Finishing CMM	186	4			176	4		
7	Radiography Test	125	3.2			220	5		
8	Final inspection	65	2			63	2		

Table 5: Results of the fifth and sixth runs that did not created significant change in the output

Row	Work station	Fifth Run				Sixth Run			
		Average Number Waiting (pc)	Average Time Waiting (day)	Average WIP	Outputs	Average Number Waiting (pc)	Average Time Waiting (day)	Average WIP	Outputs
1	Wax CMM	80	1.2	B-643	A+456	80	1.2	B-690	A+529
2	VIMs	150	2.5			153	2.5		
3	*Core Leach*	294	9			300	9.1		
4	Cleaning	142	3			142	3		
5	FPI Defect Removal	165	3.5			161	3.6		
6	Finishing CMM	177	4			177	4		
7	Radiography Test	165	4			168	4		
8	Final inspection	63	2			64	2.1		

Table 6: Runs seven and eight with small changes have slightly increased the output

Row	Work station	Seventh Run				Eighth Run			
		Average Number Waiting (pc)	Average Time Waiting (day)	Average WIP	Outputs	Average Number Waiting (pc)	Average Time Waiting (day)	Average WIP	Outputs
1	Wax CMM	80	1.2	B-690	A+529	80	1.2	B-895	A+667
2	VIMs	153	2.5			150	2.5		
3	*Core Leach*	300	9.1			294	9.1		
4	Cleaning	142	3			142	3		
5	FPI Defect Removal	161	3.6			160	3.5		
6	Finishing CMM	177	4			177	4		
7	RT	168	4			168	4		
8	Final inspection	64	2.1			63	2		

Table 7: The last run and the optimal amount show the number of parts in the queue as well as the maximum output

Row	Work station	Ninth Run				Tenth Run			
		Average Number Waiting (pc)	Average Time Waiting (day)	Average WIP	Outputs	Average Number Waiting (pc)	Average Time Waiting (day)	Average WIP	Outputs
1	Wax CMM	80	1.2	B-890	A+663	80	1.2	B-943	A+670
2	VIMs	150	2.5			150	2.5		
3	*Core Leach*	294	9			294	9		
4	Cleaning	142	3			142	3		
5	FPI Defect Removal	160	3.5			165	3.5		
6	Finishing CMM	177	4			177	4		
7	RT	168	4			165	4		
8	Final inspection	63	2			63	2		

Table 8: Three field data for validation

Fields for validation	Month 1	2	3	4	5	6	7	8	9	10	11	12
Sales needed plan	700	1000	826	1005	1100	1025	1400	1400	1500	1300	1100	1005
Annual plan balanced with Simulation	686	950	826	1005	1000	1025	1375	1242	1320	1490	1062	1005
Actual number produced in twelve months	686	660	826	1005	719	1025	1375	1242	1493	1490	1062	1005

Table 9: Analysis of Variance (ANOVA)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
year	2	24904	12452	0.18	0.832
Error	33	2224633	67413		
Total	35	2249537			

Table 10: Plan format

Row	Products	M1	M2	.	.	.	Mj	Op time (M_t)	Ms	H
1	product 1	M11	M21	.	.	.	Mj1	M_{t1}		
2	product 2	M12	M22	.	.	.	Mj2	M_{t2}		
3	product 3	M13	M23	.	.	.	Mj3	M_{t3}		
4	.	.	.	.	.	.	.	.		
5	.	.	.	.	.	.	.	.		
6	.	.	.	.	.	.	.	.		
7	product q	M1q	Nq2	.	.	.	Mjq	M_{tq}		

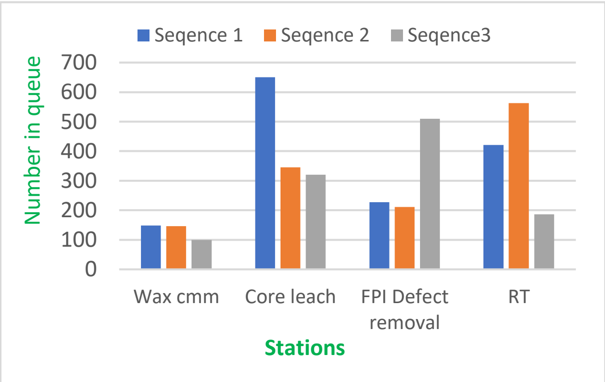

Fig.1 Average number waiting (Y-axis) due to different sequences in some stations (X-axis), which indicates the effect of product program sequence on stations and production queue balance

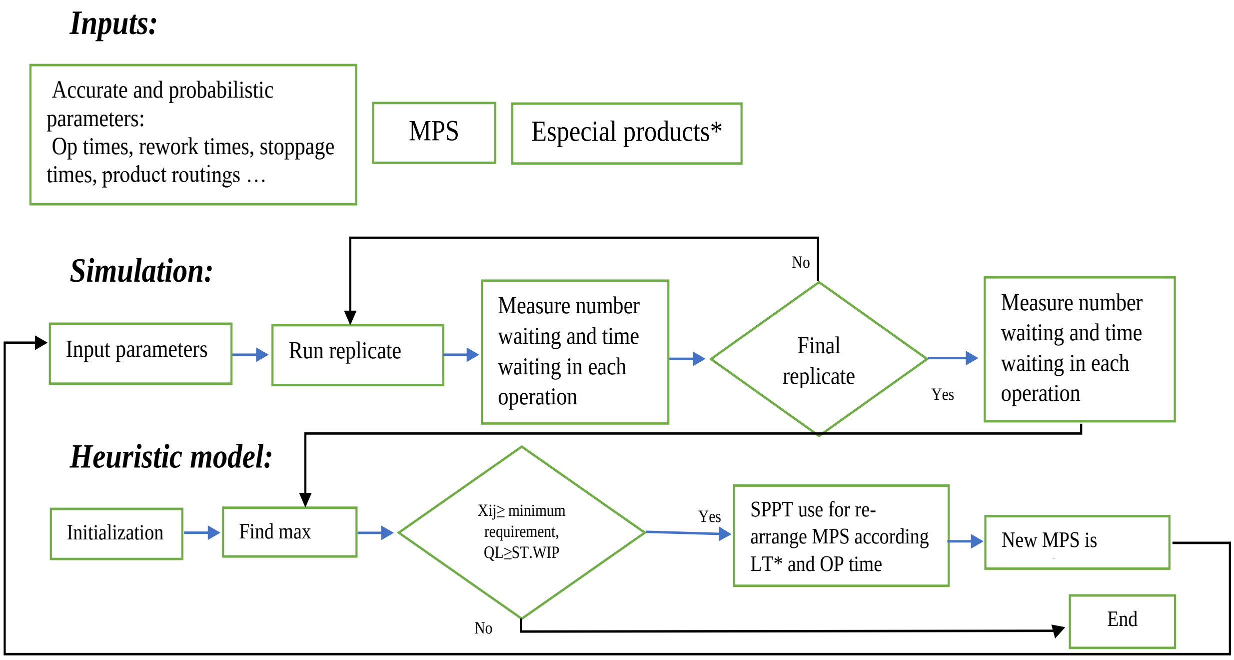

Fig.2 The research method

* **Special product** is kind of parts like new-part development which has “must finish on” constraint.
***LT**: The time it takes for a product to be produced.

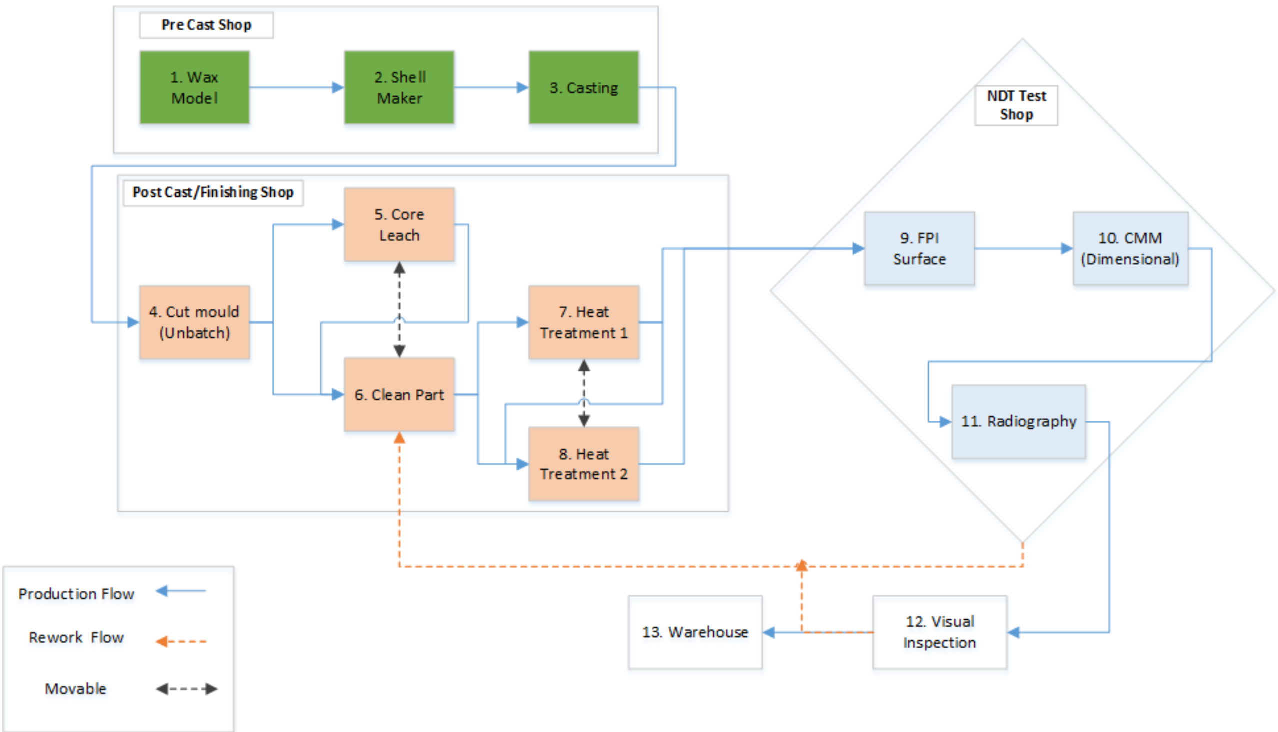

Fig.3 Flow Process Diagram

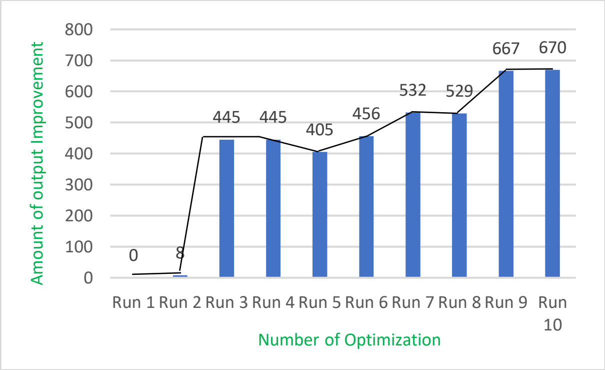

Fig.4 With the implementation of the algorithm, the amount of increase of outputs, which is the main purpose of the article, is showed. it starts from the first execution (zero value) which is the basis of the improvement and ends with execution 10 which is the end of the algorithm.

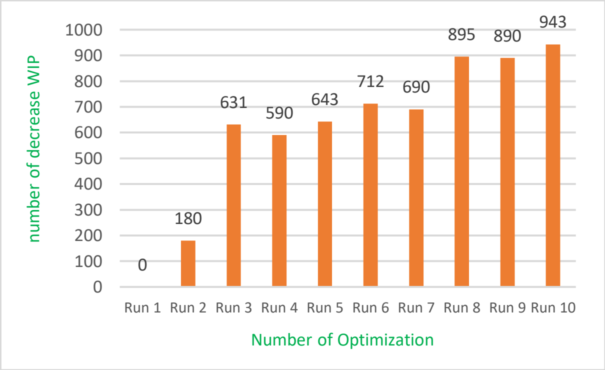

Fig.5 With the implementation of the algorithm, the amount of decrease WIP is showed. it starts from the first execution (zero value) which is the basis of the improvement and ends with execution 10 which is the end of the algorithm.

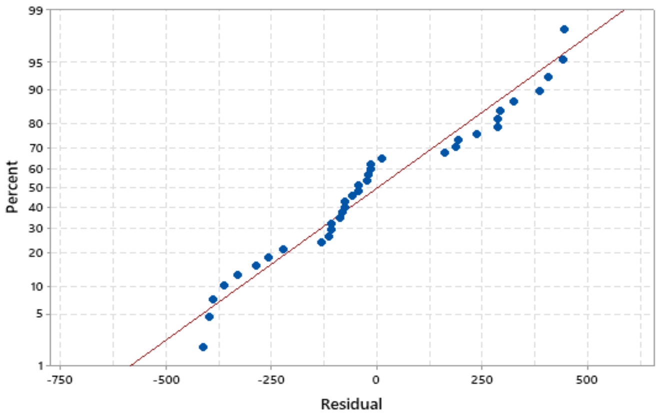

Fig.6 residual chart which showed that the production, order and sales order to be very close to predict and indicate the correct operation of the model in optimizing and meeting customer needs.

Technical biography:

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