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# *A simulation –based approach for optimizing an electro-plating production process based on theory of constraints and data envelopment analysis*

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## Abstract

Evaluating and developing the electroplating production process is a key challenge in this type of process. The process is influenced by several factors, such as process parameters, process costs, and production environments. Analyzing and optimizing all these factors together requires extensive analytical techniques that are not available for real-case industrial entities. This paper presents a practice-based framework to improve the electroplating production line performance in order to reduce product flow time and waiting time while increasing total throughput with minimum number of defective products so as to establish sustainable operations and improve system performance. The proposed approach respectively uses Design of Experiments (DOE), Discrete-Event Simulation (DES), and Theory of Constraints (TOC) to identify the most significant factors affecting the production process and simulate a real production line to recognize the effect of these factors and assign possible bottlenecks. Several scenarios are generated as a corrective strategy for improving the production line. Following that, Data Envelopment Analysis- Charnes, Cooper, and Rhodes (CCR) input-oriented DEA model is used to evaluate and optimize the suggested scenarios.

**Keywords:** Electroplating process, Simulation, Design of Experiment (DOE), Performance Optimization, Theory of Constraints (TOC), Data Envelopment Analysis (DEA).

## 1. Introduction

Electroplating is the process of coating a surface with a thin layer of metal to improve the surface quality for a specific application [1]. Multiple phases of processing are necessary to complete the coating process, with each stage requiring certain parameters to control the quality and the thickness of the coating. One of these parameters is time; if the processing time exceeds a specified amount at each stage, the coated layer thickness, the consumption of the coating materials and the electrical current may be affected, accordingly increasing the overall cost and energy consumption of the process. In general, plating thickness is proportional to plating duration and current [2]. Faraday's Laws state that the quantity of charge flow Q in a solution is proportional to the current flow I and flow time T, as demonstrated in the following equation: $Q=IT$ [3].

Whether the coated material is metal or plastic, a variety of factors influence product flow time in an electroplating production line. These factors include plating tank capacity, operator allocation, rack structure and amount, and so on. Materials costs and associated energy costs are also significant factors to consider. Modeling and optimizing electroplating manufacturing lines with mathematical models to determine the effect of these parameters on process performance is both difficult and inefficient. Simulation generates more accurate results and is more adaptable than mathematical models. Simulation-based optimization is commonly employed in companies with a manufacturing heritage to handle decision-making difficulties connected to process and system improvement.

This work's main objective is to increase the efficiency of the electroplating production line in order to quote short and reliable lead times, decrease waiting times, and increase overall throughput while minimizing defective product counts in order to develop sustainable operations by applying an integrated simulation-based experimental design and Data Envelopment Analysis (DEA).

An actual electroplating production process was modelled, tested, and validated for this purpose. Regression analysis and theory of constraints (TOC) paradigm were used to identify the key factors influencing product flow time and bottlenecks.

Following that, various possible scenarios were developed based on the study of TOC and regression models. DEA was created for scenario analysis. In addition, the Charnes, Cooper, and Rhodes (CCR) DEA model was employed for the evaluation and optimization process. The major indicators utilized to measure the system's performance were lead time/product flow time, waiting time, and resource utilization.

## 2. Literature review

Identifying the status of the production line and current system performance is a difficult task that any make-to-order (MTO) company may face. In the literature review, a number of methodologies for modelling the manufacturing system and its performance is investigated. Existing approaches in this discipline are classified into two types: theoretical or analytical approaches and experimental approaches. Analytical approaches used mathematical models-based assumptions and algorithms to solve any manufacturing problem. However, these approaches were limited in that they only considered very simple manufacturing systems and a limited number of parameters and presumptions, without taking into account all manufacturing status, as discussed in [4–9]. The experimental approaches, on the other hand, often used simulation or real-world data to create a model that approximated the system features and performance outlined which discussed in [10–16]. The based optimization strategy is frequently employed in many studies for improving the overall efficiency of identically processes or the overall performance of a system illustrated in [17-24].

Any production system has its own limitations and system constraints. Bottlenecks should be examined regularly in order to produce quick solutions to overcome these limitations for system performance optimization, ensuring long-term customer satisfaction and increasing system performance. Since Goldratt published the notion of constraints in the mid-1980s, much work has been expended on determining the optimal methods for constraint identification and approaches to eliminate constraints in order to improve production performance. This idea has been the subject of extensive investigation, with applications in a variety of domains [24–28].

The majority of studies in the electroplating optimization area are devoted to optimizing the chemical composition and process parameters such as temperature, current, voltage of coating, and coating thickness to obtain high quality coating as observed [29–32]. Other studies concentrated on electroplating production line process operations and management optimization including many techniques, such as an extensive mixed integer linear programming model, were created to identify optimization techniques for the single-hoist cyclic scheduling issue for electroplating lines [33]. A triple-objective combined dynamic optimization (MIDO) model was created as a consequence of addressing output optimization, energy savings, and wastewater reductions concurrently for the best design and operation of electroplating operations. The 3D Pareto border of the optimization issue is obtained by iteratively solving the MIDO model using a tried-and-true approach, which offers crucial professional guidance for the process design and operation of electroplating processes [34]. A tolerance-based rule-base system was also suggested in order to reduce the completion time without a defective product and increase throughput for a single-crane scheduling challenge in a flexible circuit board electroplating line [35].

None of the preceding articles presented a real framework and application for introducing simulation-based optimization, integrated with design of experiments and theory of constraints, to evaluate and optimize the electroplating production process in terms of product flow time, material costs, and energy costs. The primary goal of this work is to improve electroplating production line performance in order to quote a short and reliable lead time and reduce the waiting time while increasing total throughput without defective products so as to establish sustainable operations.

## 3. Work methodology

The suggested framework for this study is presented in figure 1. Accordingly, the framework had five main steps: designing production flowcharts; designing and verifying simulation models; investigating significant factors based on experimentally designed simulation; conducting TOC to deduce bottlenecks; designing optimization scenarios based on factors and bottlenecks; and selecting the best scenario.

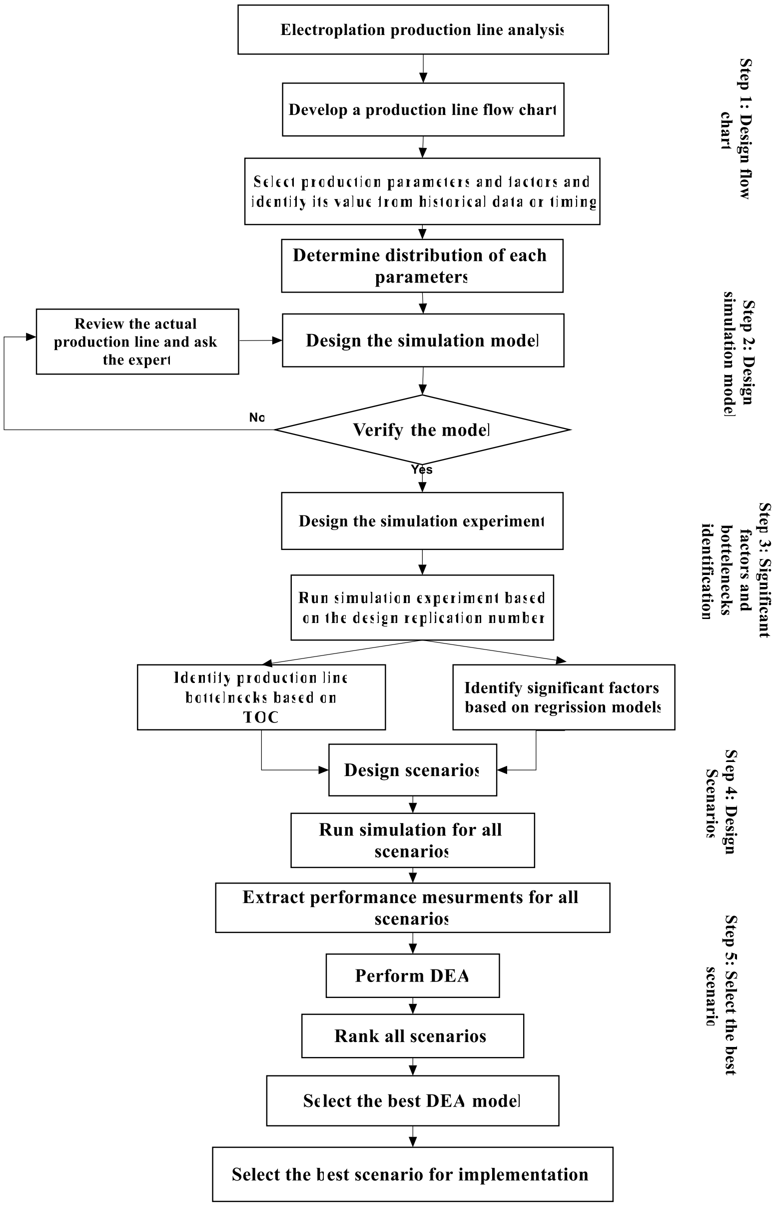


Figure 1. Overview of methodology

### 3.1. Problem and case study identification

This study is being carried out in a plastic products MTO manufacturing company, where various products undergo several manufacturing stages such as injection, coating (plating), printing, and painting, as each product requires its own production route. After reviewing the historical data in the company's enterprise resource planning system, it was determined that all production stages are stable with little lateness, with the exception of the electroplating production stage, where lateness and work-in-process (WIP) have increased significantly. The system recorded a delayed order as a result of the second processing stage, which is considered a bottleneck in the production process. The historical data from the electroplating production line showed a high rate of defective products, WIP, cost increases, and product lead times, all of which contributed to a reduction in the performance of the manufacturing system as a whole. Based on data analysis of the KPI in the manufacturing system under service level constraints, the company needs to optimize the electroplating production line to maximize system performance in order to quote short lead time, decrease the number of late jobs, decrease product flow time, and decrease WIP in the system at the lowest possible improvement cost.

The electroplating production line, as depicted in figure 2, involves a number of processes, including product and rack setup and fixation; acid cleaning; etching; neutralization; electrical plating; precipitation; pre-dipping, activation; nickel and chrome deposition. Various washing procedures are a part of the overall process. The final steps in the manufacturing process are drying and packaging.

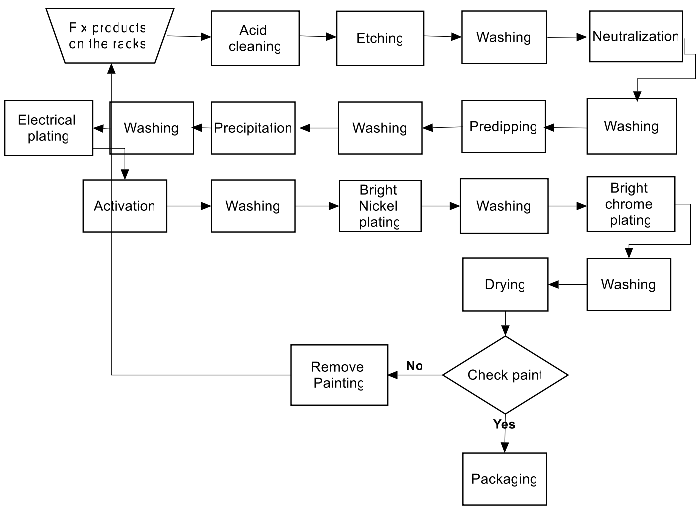


Figure 2. Electroplating production process flow chart

Two cases are examined in this study. In the first case, a maximum of eight products of the two types of products A&B are taken into consideration. Twelve workstations are used to produce these products. They each have a particular sequence and route. In this case, each product can make several visits to various processes (re-entrant flows) without having to go through additional processes. The second case involves the delivery of extremely large amounts of products to the production line, ranging from 100,000 to 500,000 units, for a specific product type that must go through 19 processing steps. Each order contains a unique set of specifications such as the number of racks, the batch size, which is determined by the size of the product, and the precise duration of each processing step. More details on how various process-related variables impact the overall product flow time are provided in the next section.

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### 3.2. Simulation model assumptions and variables

The computer simulation model is generated using the flowchart created in figure 2. Manufacturing system performance measures include throughput rate, flow time or lead-time, cost, and resource utilization. Several factors influence system performance; some are continuous and unpredictable, making adjustments difficult, such as environmental parameters and customer order amount, while others are adjustable. Six major factors are taken into consideration in this work: order arrival rate, resource capacity, processing time in each workstation (stage), batch size in each batch processing stage, time to failure (TTF), and time to repair (TTR) in each workstation subjected to random failure. The following notation will be used: The vectors $X_k$ represent the k factors, which are assumed to exist:

k= (1,2,....,6).

All system products (orders) are represented in the factors as vectors. The factors denoted as vectors include all types of orders in the system.

$\overrightarrow{X_1}$= {$\lambda_1$, $\lambda_2$, …, $\lambda_i$}; λ is the orders interarrival time, i the order type enters the system (1)

$\overrightarrow{X_2}$= {$TTF_1$, $TTF_2$, …. $TTF_j$}; TTF is the time between failure in each work station j (2)

$\overrightarrow{X_3}$= {$TTR_1$, $TTR_2$…. $TTR_j$}; TTR is the time to repair in each work station j (3)

$\overrightarrow{X_4}$= {$N_1$, $N_2$,..., Nj}: N is the number of resources in each work station j (4)

$\overrightarrow{X_5}$= $t_{ij}$; t is the processing time for each arrival order i in work station j (5)

$\overrightarrow{X_6}$= $B_j$ ; B is the batch size in each batch processing work station j (6)

## Simulation Model Assumptions and Considerations:

- Each workstation has a predetermined processing time for each product type.
- No disruption of power
- Data was gathered from the company and identified with the appropriate analyzer tool in ARENA software for data analysis to determine the fitting statistical distribution.
- The manufacturing working hours are 8 hours per shift, two shifts per day, five days a week.
- The TTR and TTF schedules have been added to the simulation model along with the machine that is exposed to random failure.
- The model is simulated for 12 workstations (WS1 to WS12).

The objective of this research is to raise the production line's performance level. The key performance indicators (KPI) should be chosen before attempting to evaluate the performance of any manufacturing system or process. In this study, the electroplating production line's performance indicators are lead time (flow time), throughput rate, waiting time (queue length), and machine utilization level. First, factors are investigated, followed by data collection for the first case study with minimum and maximum value from observation over 6 months of production, which is recorded and distributed using the input analyzer tool in ARENA software as shown from table [1-6]. Appendix A contains the detailed analysis.

## Flow Time Mathematical Model Formulation

In this study, lead time is regarded as the most essential key performance indicator, and the ability to accurately predict flow time is critical to quoting a good lead time. The time a job spends in the manufacturing process, from order release to completion, is referred to as its flow time. Waiting time or the time spent in lines is part of the acknowledgement of job flow time as playing an important role in any production process. The lead time formulation was created using the flow time due date assignment (FTDD) method, which has been shown to provide less mean value, total delay, and number of tardy jobs than other methods [36].

Flow-time FT is stated as the difference between the time at which a job enters the shop and the time at which the last operation on that job is completed. Equation [7] can be used to calculate FT by adding the processing times and waiting periods for jobs.

$FT=\sum_{j=1}^{j=n} p_{ij}+w_{ij}$ ; where j is the processing work station =1,2,3,….,n (7)

$p_{ij}$ is the total processing time of product i in workstation j

wij is the waiting time in each station j

### 3.3. Discrete Event Simulation DES

Simulation models can investigate the dynamic state of a manufacturing system and more precisely depict its properties. They can also be used to detect and solve problems in a more flexible and cost-effective manner than physical prototyping and testing. The first step in developing a simulation model is determining which aspects of a real system should be fixed (parameters) and which should be permitted to change during the simulation experiment (variables) [37].

The electroplating production line, which may include numerous workstations, batch processing, fluctuating machine capacity, random failures, WIP, and re-entrant flows, was identified as a bottleneck stage in the entire manufacturing process. This study takes a wide range of products into account. The electroplating production line, which may involve multiple workstations, batch processing, various machine capacities, random failure, WIP, and re-entrant flows, was considered a bottleneck stage in the overall manufacturing process in the study of a scale-down from a plastic injection and electroplating factory. This study considered a variety of products that need to be processed along different production routes at multiple workstations in the electroplating production line.

This work employed simulation as an analytical tool that integrated both the system and the model to better understand how the system behaves in various circumstances. The system is represented as a discrete event model. Figure 3 illustrates how a discrete-event simulation (DES) model runs in the ARENA software and how it represents the production system and its order arrivals.

The simulation model is designed to describe the actual production line with all stations present in the system, and two cases of product plating manufacture are investigated, the first of which is depicted in Figure 3. Multiple products entering the system with a limited order quantity, having a specific sequence and visiting the workstation more than once, and requiring batch processing workstations with a predetermined batch size, this case is used in factors analysis and measuring its effect on lead time or production flow time using fractional factorial analysis.

The other case considered one type of product with an extremely high order quantity, the product visits all workstations in batch processing mode, this case was employed in DEA and TOC experiments. For 10,000 hours of simulation time, 32 simulation runs are carried out in order to extend the regression model and quantify the sensitivity of the chosen response (flow time) to the chosen variables (factors). The flow time formula, as illustrated in equation 7, was inserted into the simulation model to record the flow time of each product.

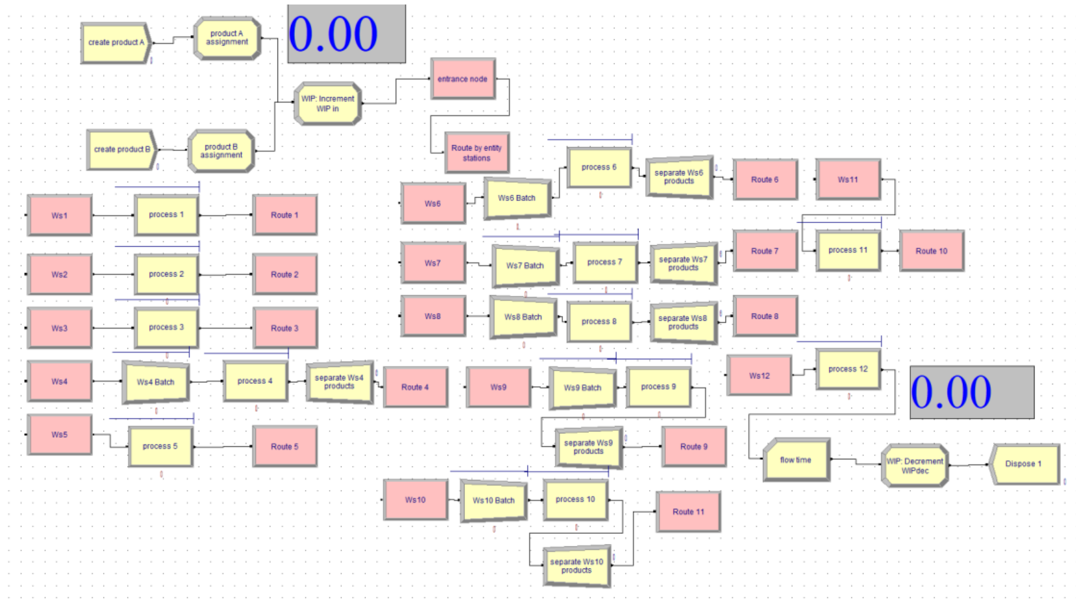


Figure 3. First Case Simulation Model for an electroplating production line

## 3.4. Design of Experiment

To identify the important factors that influence the manufacturing process; a mathematical description of the process is required. Minitab 14 is used to build a fractional factorial design. As the number of variables increases, the number of runs required to produce a replicate of the design, quickly outgrows the resources of most experimenters. As a result, fractional factorial design is used [38]. To limit the number of simulations runs, fractional factorial design resolution IV was used, as shown in Table 7, Appendix B.

### 3.4.1.Factors Levels Selection for DOE

The electroplating production line's product flow time has been chosen as one of the performance measurement indicators, and thus it is expected to be determined how various factors affect the flow time using statistical methods and experimental design. The ranges over which the design variables will be adjusted and the precise levels at which the runs will be performed must be decided after the design variables have been chosen. Based on historical data gathered over a 6-month period for the first case study, high and low design levels of factors were chosen. Coded levels are utilized to overcome the issue since each factor is represented as a vector or matrix of two different sorts of products. The codes -1 for the low level and +1 for the high level, respectively, are used to identify the two levels. The simulation is run using a fractional factorial design to determine the regression equation's significant effects on the flow time for each factor.

In order to present the effect of factors and their interactions on the system performance, fractional factorial experiment and response surface experiment data from the simulation data collected in the first case were employed to estimate the flowtime regression models. Flow time was selected as the response since it is one of the performance measures as shown in (R1) and (R2).

### Regression Equation in fractional factorial experiment

$$\text{FLOW TIME} = -33 + 916\ X1 + 53\ X2 + 233\ X3 - 314\ X4 + 524\ X5 + 4137\ X6 \qquad \text{(R1)}$$

### Regression Equation in responses surface experiment

$$\begin{aligned}\text{FLOW TIME} = {} & 886 + 292\ X1 - 545\ X2 + 136\ X3 + 88\ X4 + 44\ X5 + 2438\ X6 - 120\ X1{*}X2 \\ & - 465\ X1{*}X3 + 377\ X1{*}X4 + 198\ X1{*}X5 + 2424\ X1{*}X6 + 347\ X2{*}X3 \\ & + 278\ X2{*}X4 + 144\ X2{*}X5 + 547\ X2{*}X6 - 742\ X3{*}X4 + 837\ X3{*}X5 \\ & + 217\ X3{*}X6 - 574\ X4{*}X5 - 145\ X4{*}X6 + 355\ X5{*}X6 \qquad \text{(R2)}\end{aligned}$$

The analysis of variance (ANOVA) results for the fractional factorial and response surface experiments are reported in Tables 8 and 9 respectively, and are graphically depicted in Figures 4,5, 6, and 7, illustrated in Appendix B.

As indicated in Table 7, figure 4, and figure 5 in Appendix B, the analysis of variance table, main factors effect chart, and Pareto Chart show that X1 and X6 have the most significant effect on flow time, as F value is far bigger than P value at this point, indicating that order arrival rate and batch size are the most significant factors.

According to the values in the response surface analysis ANNOVA table, factors interaction effect chart, and Pareto chart for factor interaction as shown in table 9, figure 6, and figure 7 as shown in Appendix B, it has been shown that X1, X6, and X1X6 have the highest F value when compared to P value, indicating that X1 and X6 as well as the two-way interaction X1X6 have a significant effect on the flow time of the products in the production line.

The regression coefficients are closely related to the factor effects, as demonstrated in the two regression models X6 and X1X6, which have the highest regression coefficient, which means that the arrival rate of future orders can affect the total number seized on the system as the system has more than re-entrant workstations (visited more than one) WS 4,5,6,7,9,10, In addition to re-entrant workstations, it also has batch processing in Ws 4, 6, 7, 8, 9, and 10, which has a major effect on flow time as shown in the simulation report. The main cause of the increased flow time of products A and B is the waiting time in batch processing workstations. As shown in Tables 10 and 11, which are illustrated in Appendix B, for the fractional factorial experiment and the response surface experiment, respectively, R squared is used as a statistical measure of fit to show how much variation and correlation of a dependent variable is explained by the independent variable(s) in the regression model.

The basic standards for a good R-Squared reading can be substantially higher, such as 0.9 or above, as seen by the high level of correlation demonstrated by the Response Surface

Analysis 97.61 (0.97) R-Squared reading. The R squared demonstrated in the fractional factorial design (87.41%) can likewise be regarded as an acceptable level of correlation.

## 3.5. Theory of Constraints Approach

The Theory of constraints technique regulates throughput and utilizes the only resources which is the bottleneck to manage throughput and other performance metrics [39]. In order to better understand the system and reduce product flow time, a theory of constraints (TOC) study based on the DES model is applied. Bottleneck and non-bottleneck resources are the two categories into which TOC divides the enterprise's resources. The simulation diagnostic model (second case) is used to identify the bottleneck resource, determine the bottleneck process, and measure current system performance in order to control the bottlenecks and enhance system performance as illustrated in Figure 8, which is referred to in Appendix C.

The case being considered at this point involves a particular class of products with extremely large numbers, for which the customer established a lateness penalty cost. Each of the five batches contains 50 items that need to be coated. In this case, the batches are designated at the racks on which the product is fixed. This product goes through 19 different stages of processing, each station having a set processing time. After coating, all batches are sorted, polished, and packaged.

Measuring the usage of the production system's machines is one method for identifying the bottleneck machine; the machine with the highest utilization is thought to be the bottleneck. It can be difficult to identify the bottleneck operation when different processes are used at the same rates. Additionally, the temporary bottleneck cannot be identified using the utilization approach [40]. Measuring the "queue lengths of the machines" in the production systems is another technique, which is often used to assess the bottleneck operation. With this approach, the waiting time or queue length is measured, and the resource with the longest waiting time or queue length is deemed to be the bottleneck [41]. The longest queue length or longest waiting time is the bottleneck detection approach taken into consideration in this work. This is proved from the diagnostic simulation report in Table 12 illustrated in Appendix C. Based on data from the simulation model used for diagnosis, it may be concluded that the bottleneck process stations for acid cleaning and bright chrome have the longest lines or the highest waiting times.

## 3.6. Data Envelopment Analysis DEA

DEA is a nonparametric strategy for analyzing the relative utility of a set of decision-making units (DMUs) is based on a linear programming model that accepts a diverse range of inputs and generates a variety of different outputs; this optimization approach is widely utilized in research [42–48]. In DEA, non-beneficial criteria are referred to as input, whereas advantageous criteria are referred to as output. It is designed to have a low input value (non-beneficial criteria) and a high output value (beneficial criteria).

In general, DEA uses the idea of system efficiency optimization and derives the output or input that determines the overall efficiency of DMUs. Alternative scenarios (DMUs) are characterized in the decision matrix.

DEA was utilized as an optimization method in this work to choose the most effective scenario and enhance system performance. In this study investigation, resource utilization and throughput rate were DEA model outputs, whereas machine utilization, waiting times, and throughput rate served as optimization indicators.

To consider the basic DEA model, four DMUs, two outputs (yij), and one input (xij), were chosen.

The purpose of the model was to optimize the weighted sum of outputs to weighted sum of inputs ratio. It should be noted that $E_j$ represents the efficiency of DMU j as stated in equation [1], where vi represents the weight of input parameter i and $u_r$ represents the weight of output parameter r.

$Max\ Ej = \sum_{r=1}^{2} \text{uryrj} / \sum_{i=1}^{1} \text{vi xij}$

Subject to:
$\sum_{r=1}^{2} \text{uryrj} / \sum_{i=1}^{1} \text{vi xij} \leq 1,\ \forall\ j=1,2,3,4$

$ur \geq 0,\ \forall\ r=2$
$vi \geq 0,\ \forall\ i=1$

In order to enhance the performance of the electroplating production line in terms of the stated indicators, several scenarios or alternatives (DMUs) are built based on the recognized constraints using TOC and fractional factorial analysis in the DOE work stage. There are undoubtedly a number of more scenarios that might be stated to enhance performance, but many of them are either too costly or inappropriate for the current circumstance to be used in reality.

According to TOC, the station with the longest queue length or waiting time is designated as the bottleneck station after running the simulated model numerous times, as shown in Table 11, and the following problems turned out:

1. The first station (acid cleaning) has the longest queue due to the effect of batch processing and the arrival rate of the products.
2. The bright chrome plating queue is the longest and has the highest wait time; as a result, the batch of products (racks) must spend more time in the previous station, potentially resulting in coating defects, high chemical and electrical consumption, and an increase in total time spent in the production line or lead time.

3. Some stations have extremely high utilization rates, while others have extremely low utilization rates, resulting in an increase in system WIP.
4. The batch size (rack quantity) is too small and should be increased to improve throughput rate.
5. The throughput rate was quite low in terms of working hours.

Based on the problems identified in the simulation model report of the current state of the production line in the second case study, and with the participation of the production manager's point of view based on the existing constraints, the scenarios will be separated into four alternatives as follows:

Scenario 1: This scenario represented the production line's prior position two years ago when each station had just one resource (tank), batch size was limited to 8 racks, each rack carrying 50 products, and only one shift worked each day.

Scenario 2: the scenario identified from the current condition of the production line that increased one resource (tank) in the bright chrome station, resulting in a 50% reduction in processing time in the bright chrome station.

Scenario 3: This scenario involves changing the geometric design of the rack, which results in a rise in the number of products kept in each rack from 50 to 80, resulting in a greater throughput rate; increasing the tanks in the bright chrome station to two tanks; and working two shifts per day.

Scenario 4: This scenario proposed boosting bright chrome and pre-dipping stations, adjusting the volume of the tank (tank capacity), lowering working hours to one shift per day, and changing the geometric shape of the racks to hold 80 products to balance resource utilization.

Following scenario selection, simulations are run for each scenario, and the values of inputs and outputs are stored in the decision matrix, as shown in Table 12.

Table 12. DEA decision matrix

| DMUs (Scenarios) | Input 1 (Waiting Time) (min) | Output 1 (Machine Utilization) (%) | Output 2 (Throughput) (units) |
|---|---|---|---|
| **1** | **539.62** | **0.986** | **3400** |
| **2** | **484.95** | **0.992** | **6650** |

| | | | |
|---|---|---|---|
| **3** | **504.6** | **1.06** | **10640** |
| **4** | **410.22** | **1.07** | **17840** |
| **Nominator** $\sqrt{\sum_{j=1}^{n} X_{ij}^2}$ | **974.31** | **2.055** | **21810.76** |

After running a simulation for each alternative, the total waiting time for all processing stages was recorded. The machine utilization level for all resources was calculated from the simulation report (instantaneous utilization/scheduled utilization), and throughput was recorded as the total number of units produced.

There are various DEA models, such as the BCC and CCR models. In 1978, a linear programming (LP CCR) model was established, and it may be articulated by maximizing output or minimizing input criterion. The fundamental fractional CCR model is a non-convex programming model, which is very difficult to compute. In this study, the (LP CCR) model is used for optimization purposes to reduce the input (waiting time) to reflect on the performance of the production line, particularly the lead time quotation, which has been the case study company's biggest struggle.

To begin applying the CCR model, the decision matrix must first be normalized, which is done by dividing each value in the decision matrix by the nominator determined from the next formula, and is recorded in Table 12.

Nij=Xij/$\sqrt{\sum_{j=1}^{n} X_{ij}^2}$

The nominator = $\sqrt{\sum_{j=1}^{n} X_{ij}^2}$

The nominator is determined for each column in the decision matrix, as shown in Table 12, and then each value is divided by the nominator value, as shown in Table 13.

Table 13. The nominated decision matrix

| DMUs | Input 1 | Output 1 | Output 2 |
|---|---|---|---|
| 1 | 0.553 | 0.479 | 0.1558 |
| 2 | 0.4977 | 0.4827 | 0.3048 |
| 3 | 0.51790 | 0.5158 | 0.4878 |
| 4 | 0.42103 | 0.5206 | 0.8179 |

After the decision matrix is nominated, the CCR objective function for each DMU or alternative is determined using the following formula:

$g_k = \min\left( \sum_{i=1}^{m} v_i * x_{ik} \right)$
subject to
$-\sum_{r=1}^{s} u_r\ y_{rk} + \sum_{i=1}^{m} v_i\ x_{ik} \geq 0$ for j= 1,…..,n

$\sum_{r=1}^{s} u_r\, y_{rk} = 1$

After organising the linear programming objective function model, Hk (the efficiency measure of the Kth DMU should be calculated by using this formula:

$H_k = 1/g_k$

The nomenclature of the LP model is:

n: the number of alternatives/ DMUs
m: the number of input criteria
s: the number of output criteria
$x_{ik}$ and $y_{rk}$ denote the value of the $i_{th}$ input criterion and the $r_{th}$ output criterion for the $k_{th}$ alternative.
$u_r$ and $v_i$ are non-negative variable weights for outputs and inputs, respectively, to be determined by the solution of the minimization problem.
In this study, n = 4, m = 1, s=2
So, the objective function for each scenario is:

$\mathbf{g_1 = \min\ (0.553v_1)}$
subject to
$-0.479u_1 - 0.1558u_2 + 0.553v_1 \geq 0$
$-0.4827u_1 - 0.3048u_2 + 0.4977v_1 \geq 0$
$-0.5158u_1 - 0.4878u_2 + 0.51790v_1 \geq 0$
$-0.5206u_1 - 0.8179u_2 + 0.421030v_1 \geq 0$
$0.479u_1 + 0.1558u_2 = 1$
$u_1, u_2, v_1 \geq 0$

$\mathbf{g_2 = \min\ (0.4977v_1)}$
subject to
$-0.479u_1 - 0.1558u_2 + 0.553v_1 \geq 0$
$-0.4827u_1 - 0.3048u_2 + 0.4977v_1 \geq 0$
$-0.5158u_1 - 0.4878u_2 + 0.51790v_1 \geq 0$
$-0.5206u_1 - 0.8179u_2 + 0.421030v_1 \geq 0$
$0.4827u_1 + 0.3048u_2 = 1$
$u_1, u_2, v_1 \geq 0$

**$g_3$= min (0.51790$v_1$)**
subject to
$-0.479u_1-0.1558u_2+0.553v_1 \geq 0$
$-0.4827u_1-0.3048u_2+0.4977v_1 \geq 0$
$-0.5158u_1-0.4878u_2+0.51790v_1 \geq 0$
$-0.5206u_1-0.8179u_2+0.421030v_1 \geq 0$
$0.5158u_1+0.4878u_2= 1$
$u_1, u_2, v_1 \geq 0$

**$g_4$= min (0.42103$v_1$)**
subject to
$-0.479u_1-0.1558u_2+0.553v_1 \geq 0$
$-0.4827u_1-0.3048u_2+0.4977v_1 \geq 0$
$-0.5158u_1-0.4878u_2+0.51790v_1 \geq 0$
$-0.5206u_1-0.8179u_2+0.421030v_1 \geq 0$
$0.5206u_1+0.8179u_2= 1$
$u_1, u_2, v_1 \geq 0$

Table 14 displays the results of calculating gk and Hk for the kth scenario using the Excel solver tool to solve the linear programming model.

Table 14. $g_k$ and $H_K$ values

| Alternatives (DMUs) | $g_k$ | $H_k$ |
|---|---|---|
| 1 | 1.60864 | 0.6216 |
| 2 | 1.23589 | 0.8113 |
| 3 | 1.11706 | 0.8952 |
| 4 | 1.06587 | 0.9382 |

Table 14 shows that scenario 4, which had an effective rate of 93%, had the minimal objective function.

## 4. Results and Discussion

After examining the manufacturing line based on DOE and TOC results, the simulated model for Case 2 was activated for all scenarios. The DEA input-oriented CRR model's objective is to minimize the input (waiting time) to decrease the product flow time, whereas the waiting time is a significant portion of the flow time equation, which reflects on reducing the lead time of the entities or products, and therefore on the overall system performance. The objective function is constructed for all scenarios using the linear programming CCR model, and the results are given in table 14. The DEA deemed scenario 4 to be the optimum scenario, with an efficiency rate ($H_k$) of 93% and the least input value or objective function ($g_k$).

Despite maintaining one shift per day in this scenario, the throughput rate increased from 3400 products to 17840. This means that the throughput rate increased by 424.705 percent from the production line's previous state ((17840-3400)/3400*100). As a result, this will reduce labor costs and the overall cost of electricity utilized, as well as minimize lead-time and boost customer satisfaction.

It is predicted that modifying the rack's geometric design to accommodate more products will increase product quantity while having no effect on batch processing; the batch will grow by 42.2 percent from 8*50 to 8*80 (8 racks); each rack includes 80 products. This greatly reduces the lead-time and improves system performance.

It is recommended to increase the number of tanks in the bright chrome station and change their capacity to reduce queues and ensure that products do not have to wait in the previous station, which also reduces coating defects and chemical material consumption. It is also recommended to increase one tank in the pre-dipping station to balance resource utilization.

According to this research, managers can make better decisions when they choose the proper scenario. For example, when scenario 4 is implemented, there will be a considerable improvement in the operational performance of the production line. Managers can use this study to focus on a small number of indicators for future improvement and policy formulation.

## 5. Conclusion and Recommendations

It is challenging to determine and improve the electroplating production line's performance in order to quote short and reliable lead times while increasing throughput rate with the least amount of waiting time. This is because the production line process is not only subject to the inherent randomness of the production process, but it can also depend on a wide range of factors that can have an impact on how well the process as a whole performs.

A comprehensive framework of approaches was built in this study to fully analyze the effects that the factors may have on the performance and work on enhancing this performance based on this factor. The performance of an electroplating production line was improved by utilizing a novel methodology created by combining simulation-based experimental design, DEA, and TOC methods. In order to achieve this, a real electroplating production line was simulated, validated, and confirmed. All factors affecting production line performance were analyzed, and the significant factors were selected based on experimental design and statistical modelling. Finally, all bottlenecks were identified based on TOC as the largest queue or the longest waiting time process. Following that, four basic scenarios based on identified bottlenecks and significant factors were developed with the cooperation of case study company managers and specialists. Waiting time, productivity rate or throughput rate, resource productivity, and utilization were considered as production line performance measures in this study.

After selecting performance indicators and developing scenarios, DEA was created for scenario analysis and optimization. The optimum model for minimizing input was determined to be the input-oriented CCR DEA model. The DEA model considered waiting time as input, while selecting resource utilization and throughput rate as output. The ideal scenario was selected based on the DEA model results after executing the CCR model goal functions for four scenarios or DMUs and evaluating their efficiency. The fact that this scenario has the highest throughput rate and the shortest waiting time appears to be the most important reason why it was chosen as the best scenario. According to the optimization model, some criteria must be changed in order to improve the performance of the electroplating production line. For example, changing the geometric design of the rack to hold more products (more entities) and reducing the number of racks arriving at a given time; increasing one tank in the bottleneck station with the longest line; changing the tank capacity; increasing one tank in the pre-dipping station; and reducing the working time.

Planning and production managers in electroplating units can use the findings to increase the effectiveness of their production lines. They can also expand on the technique that has been outlined by adding additional interrelated scenarios for a future study. Flow time is chosen as one response in this work to evaluate the impact of other factors on it. It is also recommended to extend more parameters to acquire more efficient results and to employ multi-response factors in fractional factorial analysis to determine the significant effect of multiple factors on the system's performance.

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## Appendix A. Factors Levels Selection Tables

These tables showed the minimum and maximum values of the selected factors from X1 to X6, which were gathered from the management executive system of the case study company and distributed using suitable tools, which are provided by the simulation model representing the first case study.

Table 1. Products arrival rate

| Arrival rate of entity $X_1$ | A -$X_1$ (product/min) | A +$X_1$ (product/min) | B - $X_1$ (product/min) | B +$X_1$ (product/min) |
|---|---|---|---|---|
| | Expo(300min) | Expo (600) | Expo (400) | Expo (700) |

Table 2. TTF of the electroplating production line resources.

| TTF of resources $X_2$ | -$X_2$ (min) | +$X_2$ (min) |
|---|---|---|
| WS1 | Expo (12000) | Expo (15000) |
| WS2 | Expo (12000) | Expo (12000) |
| WS3 | Expo (3000) | Expo (5000) |
| WS4 | Expo (12000) | Expo (15000) |
| WS5 | Expo (12000) | Expo (15000) |
| WS6 | Expo (12000) | Expo (15000) |
| WS7 | Expo (9000) | Expo (12000) |
| WS8 | Expo (6000) | Expo (9000) |
| WS9 | Expo (15000) | Expo (18000) |
| WS10 | Expo (12000) | Expo (15000) |
| WS11 | Expo (6000) | Expo (9000) |
| WS12 | Expo (12000) | Expo (15000) |

Table 3. TTR of electroplating production line resources.

| TTR of resources $X_3$ | $-X_3$ (min) | $+X_3$ (min) |
|---|---|---|
| WS1 | Expo (120) | Expo (420) |
| WS2 | Expo (90) | Expo (390) |
| WS3 | Expo (120) | Expo (420) |
| WS4 | Expo (300) | Expo (600) |
| WS5 | Expo (300) | Expo (600) |
| WS6 | Expo (480) | Expo (720) |
| WS7 | Expo (480) | Expo (720) |
| WS8 | Expo (120) | Expo (420) |
| WS9 | Expo (120) | Expo (420) |
| WS10 | Expo (120) | Expo (420) |
| WS11 | Expo (240) | Expo (540) |
| WS12 | Expo (60) | Expo (360) |

Table 4. Resources capacity

| Resource's capacity $X_4$ | $-X_4$ | $+X_4$ |
|---|---|---|
| WS1 | 1 | 1 |
| WS2 | 1 | 1 |
| WS3 | 1 | 1 |
| WS4 | 1 | 1 |
| WS5 | 1 | 3 |
| WS6 | 1 | 1 |
| WS7 | 1 | 1 |
| WS8 | 1 | 3 |
| WS9 | 1 | 3 |

| | | |
|---|---|---|
| WS10 | 1 | 1 |
| WS11 | 1 | 1 |
| WS12 | 1 | 1 |

Table 5. Processing time for each product in each workstation.

| Processing time X5 | Product A -X5 (min) | Product A +X5 (min) | Product B -X5 (min) | Product B +X5 (min) |
|---|---|---|---|---|
| Ws1 | Expo (5) | Expo (10) | Expo (7) | Expo (12) |
| Ws2 | Expo (15) | Expo (20) | Expo (17) | Expo (22) |
| Ws3 | Expo (20) | Expo (25) | Expo (25) | Expo (25) |
| Ws4 | Expo (15) | Expo (20) | POIS(17.5) | POIS(21.7) |
| Ws5 | 9.5 + 11 * BETA(0.068, 0.127) | 14.5 + 11 * BETA(0.068, 0.127) | 4.5 + 9 * BETA(0.154, 0.11) | 11.5 + 9 *BETA(0.154, 0.11) |
| Ws6 | 4.5 + 11 * BETA(0.105, 0.105) | 9.5 + 11 * BETA(0.105, 0.105) | 2.5 + 18 * BETA(0.13, 0.205) | 7.5 + 18 * BETA(0.13, 0.205) |
| Ws7 | 0.5 + 5 * BETA(0.0325, 0.0561) | 4.5 + 6 * BETA(0.511, 0.739) | 0.5 + 10 * BETA(0.382, 0.553) | 4.5 + 11 * BETA(0.365, 0.528) |
| Ws8 | Expo (20) | Expo (25) | Expo (15) | Expo (20) |
| Ws9 | Expo (10) | Expo (15) | 4.5 + 11 * BETA(0.105, 0.105) | 9.5 + 11 * BETA(0.105, 0.105) |
| Ws10 | Expo (15) | Expo (20) | Expo (10) | Expo (15) |
| Ws11 | Expo (15) | Expo (20) | Expo (10) | Expo (15) |
| Ws12 | Expo (40) | Expo (45) | Expo (25) | Expo (30) |

Table 6. Batch size in each workstation

| Batch size in batch processing stages X6 | - X6 | + X6 |
|---|---|---|
| Ws1 | 1 | 1 |
| Ws2 | 1 | 1 |
| Ws3 | 1 | 1 |
| Ws4 | 1 | 5 |
| Ws5 | 1 | 1 |
| Ws6 | 1 | 5 |
| Ws7 | 1 | 5 |
| Ws8 | 1 | 8 |
| Ws9 | 1 | 5 |
| Ws10 | 1 | 8 |
| Ws11 | 1 | 1 |
| Ws12 | 1 | 1 |

## Appendix B. Some Results of the Empirical Study

The simulation experiments were performed following the design of experiments resulting from applying the DOE method. Table 7 showed the fractional factorial experiment design, which discussed the number of factors and runs used in the experiment.

The analysis of variance (ANOVA) results was given in Tables 8 and 9 for fractional factorial analysis and response surface analysis, respectively. The ANOVA tables all suggest that the resulting regression models provide a good description of the data. As shown in R squared tables 10, 11.

Table 7. Fractional Factorial Experiment Design Summery

| | | | | | |
|---|---|---|---|---|---|
| Factors: | 6 | Base Design: | 6, 32 | Resolution: | VI |
| Runs: | 32 | Replicates: | 1 | Fraction: | 1/2 |
| Blocks: | 1 | Center pts (total): | 0 | | |

Table 8. ANNOVA Table for Fractional Factorial Experiment

| Source | DF | Seq SS | Contribution | Adj SS | Adj MS | F-Value | P-Value |
|---|---|---|---|---|---|---|---|
| Model | 6 | 147088137 | 87.41% | 147088137 | 24514690 | 28.93 | 0.000 |
| Linear | 6 | 147088137 | 87.41% | 147088137 | 24514690 | 28.93 | 0.000 |
| X1 | 1 | 6706550 | 3.99% | 6706550 | 6706550 | 7.92 | 0.009 |
| X2 | 1 | 22203 | 0.01% | 22203 | 22203 | 0.03 | 0.873 |
| X3 | 1 | 435776 | 0.26% | 435776 | 435776 | 0.51 | 0.480 |
| X4 | 1 | 790320 | 0.47% | 790320 | 790320 | 0.93 | 0.343 |
| X5 | 1 | 2196105 | 1.31% | 2196105 | 2196105 | 2.59 | 0.120 |
| X6 | 1 | 136937183 | 81.38% | 136937183 | 136937183 | 161.63 | 0.000 |
| Error | 25 | 21181289 | 12.59% | 21181289 | 847252 | | |
| Total | 31 | 168269426 | 100.00% | | | | |

The factors' effects and their interaction on products’ flow time were shown in figures 4,5, 6, and 7 respectively, which showed that X1, X6, and their interaction are the most significant factors.

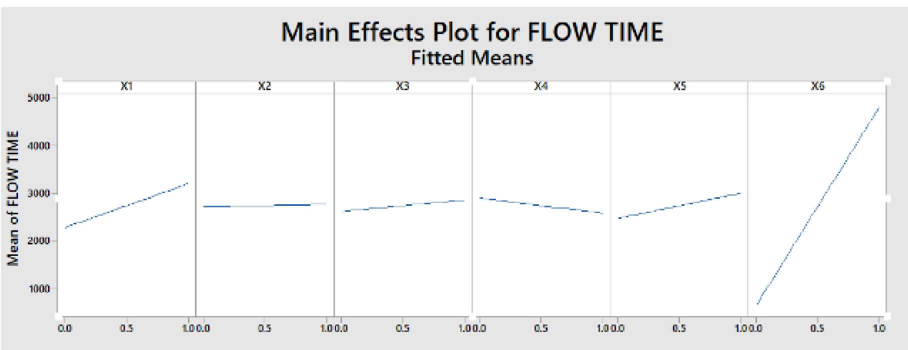


Figure 4. Main Factors effect on flow time

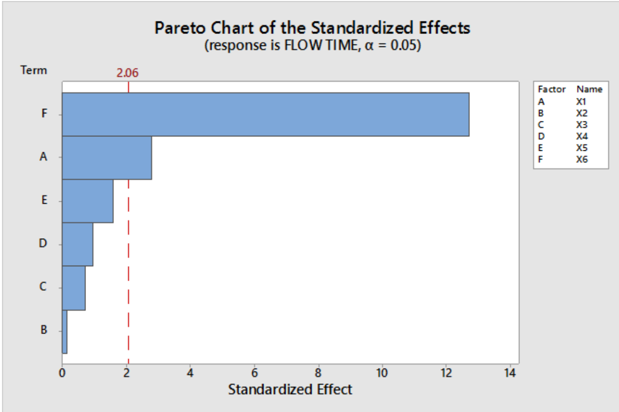


Figure 5. Pareto Chart for Factors Effects

Table 9. ANNOVA Table for Response Surface Analysis

| Source | DF | Adj SS | Adj MS | F-Value | P-Value |
|---|---|---|---|---|---|
| Model | 21 | 164253221 | 7821582 | 19.48 | 0.000 |
| Linear | 6 | 147088137 | 24514690 | 61.04 | 0.000 |
| X1 | 1 | 6706550 | 6706550 | 16.70 | 0.002 |
| X2 | 1 | 22203 | 22203 | 0.06 | 0.819 |
| X3 | 1 | 435776 | 435776 | 1.09 | 0.322 |
| X4 | 1 | 790320 | 790320 | 1.97 | 0.191 |
| X5 | 1 | 2196105 | 2196105 | 5.47 | 0.041 |
| X6 | 1 | 136937183 | 136937183 | 340.96 | 0.000 |
| 2-Way Interaction | 15 | 17165084 | 1144339 | 2.85 | 0.050 |
| X1*X2 | 1 | 28747 | 28747 | 0.07 | 0.794 |
| X1*X3 | 1 | 432762 | 432762 | 1.08 | 0.324 |
| X1*X4 | 1 | 284658 | 284658 | 0.71 | 0.420 |

| | | | | | |
|---|---|---|---|---|---|
| X1*X5 | 1 | 78719 | 78719 | 0.20 | 0.667 |
| X1*X6 | 1 | 11755310 | 11755310 | 29.27 | 0.000 |
| X2*X3 | 1 | 240603 | 240603 | 0.60 | 0.457 |
| X2*X4 | 1 | 154087 | 154087 | 0.38 | 0.549 |
| X2*X5 | 1 | 41274 | 41274 | 0.10 | 0.755 |
| X2*X6 | 1 | 599195 | 599195 | 1.49 | 0.250 |
| X3*X4 | 1 | 1100119 | 1100119 | 2.74 | 0.129 |
| X3*X5 | 1 | 1402503 | 1402503 | 3.49 | 0.091 |
| X3*X6 | 1 | 94067 | 94067 | 0.23 | 0.639 |
| X4*X5 | 1 | 659434 | 659434 | 1.64 | 0.229 |
| X4*X6 | 1 | 41766 | 41766 | 0.10 | 0.754 |
| X5*X6 | 1 | 251841 | 251841 | 0.63 | 0.447 |
| Error | 10 | 4016204 | 401620 | | |
| Total | 31 | 168269426 | | | |

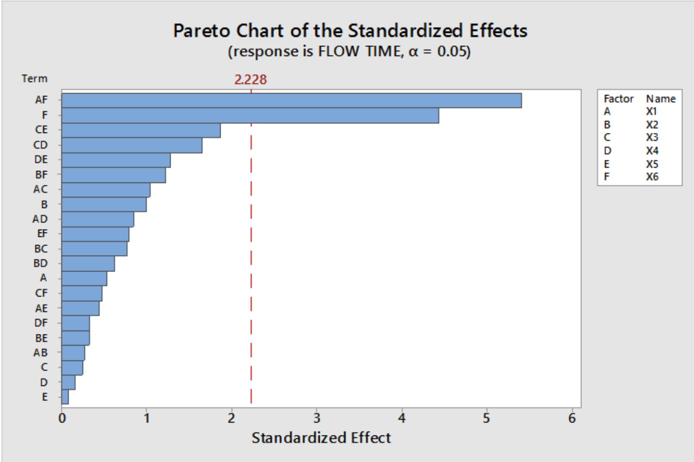


Figure 6. Pareto Chart for Factors Interaction

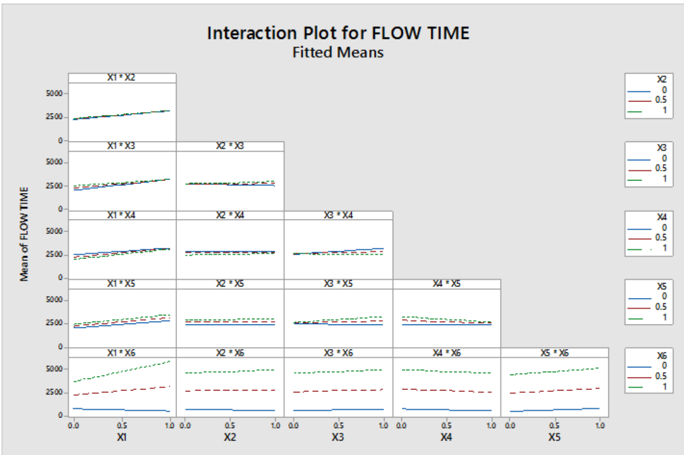


Figure 7. Factors Interaction Effect

Table 10. R- sq for fractional factorial design

| S | R-sq | R-sq(adj) | PRESS | R-sq(pred) |
|---|---|---|---|---|
| 920.463 | 87.41% | 84.39% | 34703423 | 79.38% |

Table 11. R-sq for response surface analysis

| S | R-sq | R-sq(adj) | R-sq(pred) |
|---|---|---|---|
| 633.735 | 97.61% | 92.60% | 75.56% |

## Appendix C. Some Results from the Second Case Simulation Model

Table 12. Queues waiting time in the electroplating production line

| Waiting Time | Average | Half Width | Minimum Value | Maximum Value |
|---|---|---|---|---|
| Acid Cleaning Queue | 3.7984 | (Insufficient) | 0.00 | 7.5888 |
| Activation Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Bright Chrome Plating Queue | 2.7418 | (Insufficient) | 0.00 | 5.4833 |
| Bright Nickel-Plating Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Drying Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Electrical Plating Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Etching Queue | 1.1772 | (Insufficient) | 0.00 | 2.3691 |
| Evacuating and Packing Queue | 0.05833333 | (Insufficient) | 0.00 | 0.1167 |
| Grouping Queue | 0.00099800 | 0.000015857 | 0.00 | 0.01666667 |
| Neutralization Queue | 0.00000000 | (Insufficient) | 0.00 | 0.00000000 |
| Pre-Dipping Queue | 0.1055 | (Insufficient) | 0.00 | 0.2103 |
| Precipitation Queue | 0.00475913 | (Insufficient) | 0.00 | 0.04014431 |
| Washing 1.1 Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Washing 1.10 Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Washing 1.11 Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Washing 1.12 Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Washing 1.2 Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Washing 1.3 Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Washing 1.4 Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Washing 1.5 Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |

| | | | | |
|---|---|---|---|---|
| Washing 1.6 Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Washing 1.7 Queue | 0.07306787 | (Insufficient) | 0.00 | 0.1942 |
| Washing 1.8 Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |
| Washing 1.9 Queue | 0.00 | (Insufficient) | 0.00 | 0.00 |

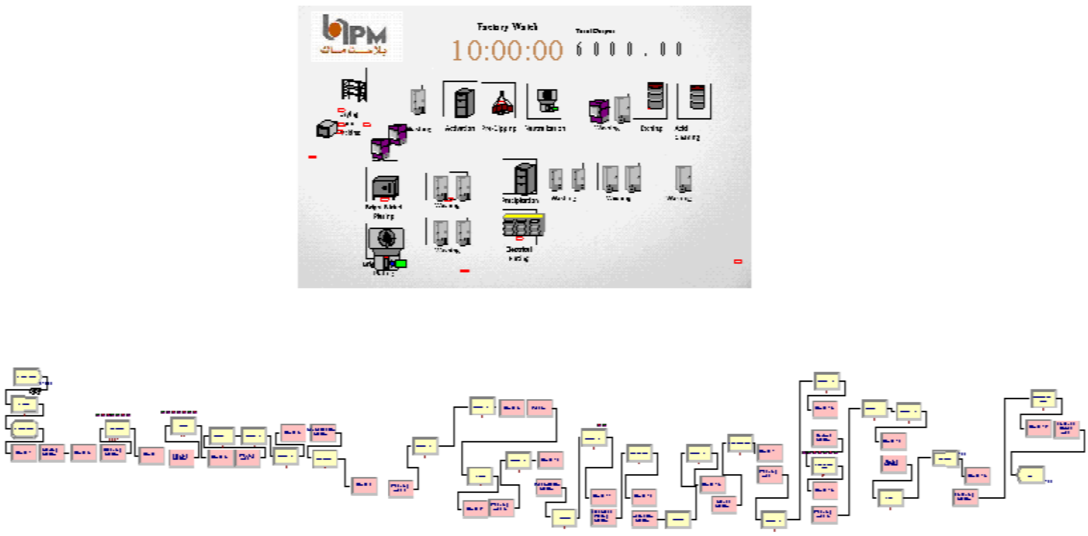


Figure 8. Second Case Diagnostic Simulation Model