# ME555 Design Optimization

## Chassis Manufacturing Line Optimization

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## INTRODUCTION

The motivation of the project comes from a plant visit of a GM chassis assembly line at Flint, Michigan. During the plant visit, we were pondering how the assembly line can manage to adjust itself to different types of chasses. The ratio of the manually operated stations and the automated stations (automation level) would play an important role for the reconfigurable manufacturing assembly line, which is also extremely important in China, where there are over 100 automakers. Our objective becomes to determine the best automation level for the chassis assembly line, which meets the desired productivity and quality levels at the lowest cost when demand is fluctuating.

## EXECUTIVE SUMMARY

We are trying to maximize the profit for our chassis company while meets the requirement of market demand. Profit is defined as the difference between the production revenue and reconfiguration cost, and cost of waste. The whole system consists of four subsystems, and the layout is shown in Fig. 1 on pg.4. The first two subsystems will find the revenue of the chassis manufacturing line. The first subsystems is to optimize the production rate. It is known that the demand for different types of product is always changing in day to day. However, the production rate for the assembly line to produce product is constant, we cannot change the production rate after setting the line. Therefore, we want to find the optimal production rate for each product so that the difference between the overall products that manufactured in a time span and the overall demand can reach zero, i.e. the system is trying to minimize the producing of unwanted product after satisfying the market demand. The second subsystem is marginal profit optimization, there are several factors affecting the marginal profit of the chassis such as material, building, energy and tooling. This subsystem wants to find which factor would influence the marginal profit most in both positive and negative way. Based on that, we can maximum the marginal profit per chassis. Our third subsystem is reconfigurable cost optimization. Our chassis company only owns one production line, which means the factory has to make a switch when market demand is changing. This subsystem takes human labor, machine and side benefit into consideration to find the optimal number of switches and ratio of human over machine and then minimizing the reconfigurable cost. The fourth subsystem is minimizing the cost of waste. There is no manufacturing system is 100% reliable, the line would inevitably produce products that cannot meet the quality because of the reliability. The minimum cost of waste would be given by this subsystem.

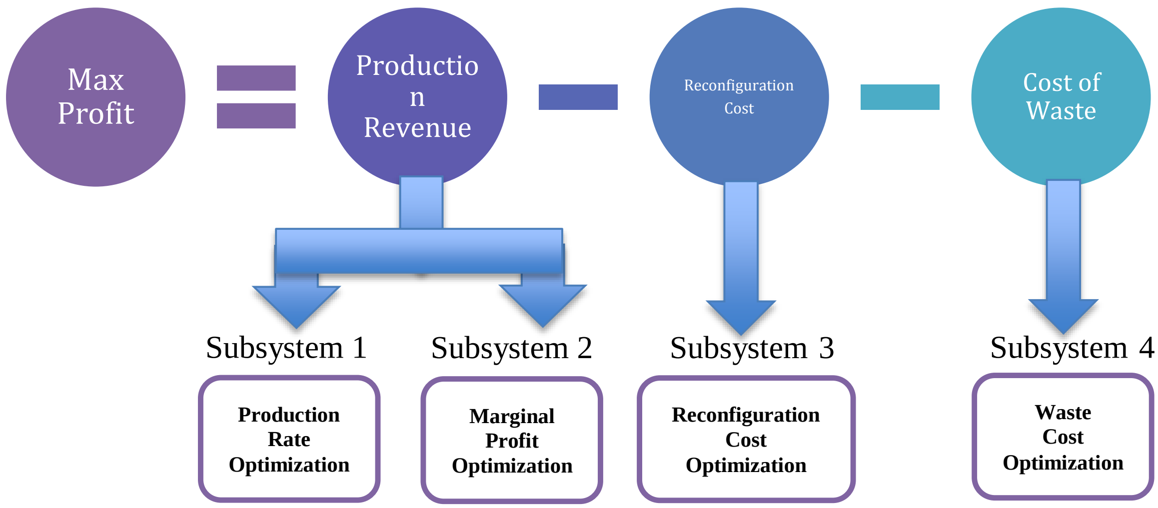


Fig. 1: Layout of the Subsystems.

After having all of the subsystems, we could combine them together to get the system – level optimal point, which is the maximum profit that we could make in one year.

### Subsystem 1-Production Rate Optimization

The product life cycles are getting shorter with the rapid changes of the market. To optimize a reconfigurable assembly line, the RMS key-design factors, i.e. production rate is considered due to uncertain demands of product families.

### Optimal Analysis

Manufacturing capacity (discrete horizontal lines) must follow market demand fluctuations (continuous curve) for a product type during its life cycle. On the other hand, production rate $P(t)$ is always not greater than capacity $C(t)$ and demand rate $D(t)$ as follows:

$$P(t) \leq \min(C(t), D(t))$$

In the balance of simultaneously producing a number of products within a family, the sum of production rates at any reconfiguration stage must not exceed the maximum feasible capacity of the RMS[1].

In our case, we are responsible to meet the demand requirement of the market. Since our maximum feasible capacity of the system is less than the maximum market demand, an optimal production rate need to be decided to satisfy the changing market demand and fit for different Chassis. The changing cycle of the demand is one year.

**Demand satisfied optimization**

To satisfy the demand, one approach is to minimize the difference between production rate and demand. The relationship between production rate and demand in one year is shown by Fig 1.1.The yellow region represents the unsatisfied demand while the blue region represents the excess capacity. Our solution is to minimize the difference between these two regions.

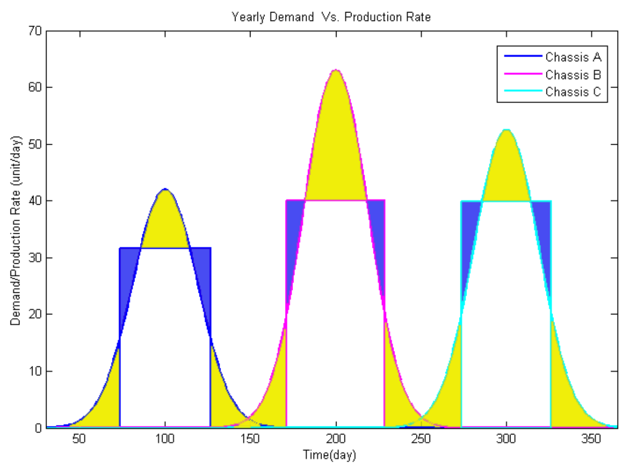


Fig 1.1: Relationship between demand and production rate

**Formulation**

In our case, demand is forecast by normal distribution and the production rate is expressed by car-box function which is defined by Weibull function. The specific parameter data is shown by table.1.1.

$$min \sum_{Prod=A}^{B,C} \sum_{t=1}^{365} \left(Demand(t, prod) - ProductionRate(t, h, prod)\right)^2$$

$$Demand(t, h) = C_{prod} * normpdf(t, \mu_{0_{prod}}, \sigma_{prod})$$

$$ProductionRate(t, h) = \begin{cases} h, & |t| \leq \Delta t \\ 0, & otherwise \end{cases}$$

Variable:

I. Time: t

II. Max production rate: h

III. Type of chassis: prod

Parameter:

I. Total demand of a certain chassis: $C_{prod}$

II. Standard deviation of a certain chassis: $\sigma_{prod}$

III. Mean of a certain chassis: $\mu_{0_{prod}}$

| Type of product | A | B | C |
|---|---|---|---|
| Total demand(unit/year) | 2000 | 3000 | 2500 |
| Pdf Function | $Normpdf(t, 100, 19)$ | $Normpdf(t, 200, 19)$ | $Normpdf(t, 300, 19)$ |

Table 1.1: Model parameter specific data

**Constraints**

The maximum production rate/ capability is less than the market demand. The constraint will be:

$$h_{prod} \leq 0.90 * \frac{\mathrm{C_{prod}}}{\sqrt{2\pi}\ \sigma_{prod}}$$

The production time interval should less than 99.73% of the demand time interval. The constraint will be:

$$2\left(\mu_{0_{prod}} - \Delta t\right) \leq 99.73\% * TimeInterval(Demand(t))$$

$$i.e., 0 \leq \Delta t \leq 3\sigma_{prod}$$

**99.7% is based on 3-sigma control limit.

### Results

By applying MATLAB fmincon function, the optimal production rate for three chassis are 31.632 units/day, 39.999 units/day and 39.812 units/day and their corresponding lead time are 53.136 days/year, 57.597 days/year and 52.954 days/year. The optimal results have been verified by Mathematica. Fig 1.2 shows the optimized result of production rate for chassis line.

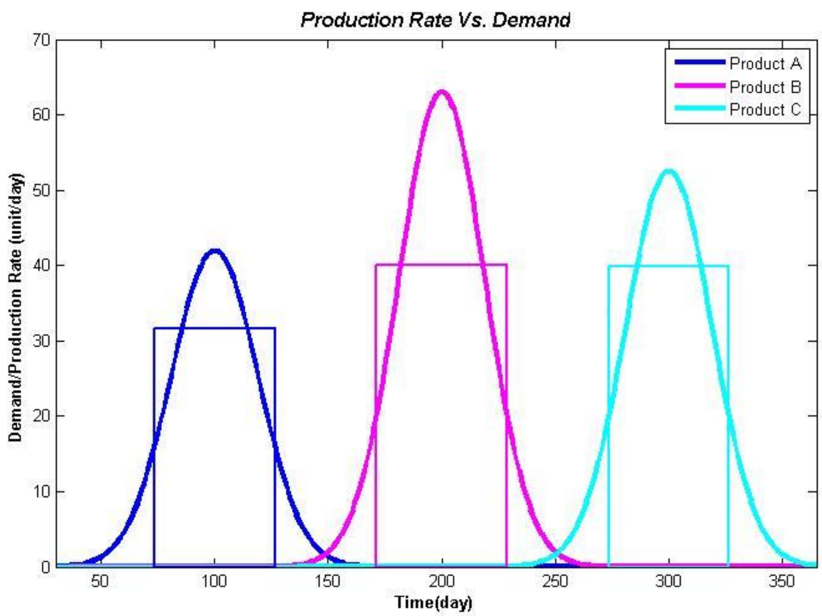


Fig 1.2: Optimized Results

## Subsystem 2- Optimization of the Marginal Profits of Other Factors

### Introduction

Subsystem 2 is a data-driven model, which looks into how factors other than human labor cost and machine cost affect the profit of the assembly line. We wanted to know the additional profit that will be generated by increasing each of the six factors by one unit. The target was to fit the marginal profit data with both linear modeling method and non-linear modeling method, and with the model, we can predict the profit based on our assumption. The exact data of the assembly line we researched on was really hard to find. To increase the credibility of the data, we found the average marginal profit breakdown of the automotive assembly line [2], and the 2013 financial report of GM [3]. The cost factors we considered are: Shipping/Receiving cost, Inspection and Testing cost, Material cost, Maintenance cost, Building cost, and Energy cost.

*Shipping/Receiving cost* ($\beta_1$)

Account for the cost during transporting parts of the chassis from suppliers, as well as packaging and containers.

*Inspection and testing cost* ($\beta_2$)

Account for the cost incurred to identify poor quality products before shipment to customers. It includes scrap cost, loss cost, rework cost and failure analysis cost.

*Raw Materials* ($\beta_3$)

Account for all the raw materials used in the production of a chassis. The final value considers the cost of primary and secondary materials. The primary raw material for a chassis is either coil steel or steel.

*Maintenance Costs* ($\beta_4$)

Account for the cost necessary for retaining or restoring the equipment or system to the specified operable condition to achieve its maximum useful life.

*Building Costs* ($\beta_5$)

Account for the costs associated to value of the land and construction cost equivalent to the space occupied by the manufacturing and auxiliary equipment.

*Energy* ($\beta_6$)

Account for the costs of the energy consumed by the equipment directly associated to the manufacturing process. This value is either based on information relative to energy consumption or on the analysis of the physical principles of the manufacturing process.

**Modeling**

Having the raw data, we shuffled and splitted the data into training and testing data sets according to a 75%, 25% splitting rule using MATLAB random seed=1. The first 75% of the data was used for training and last 25% for testing. Then, we standardized the data on both the training and test set by only using the mean and standard deviation of the training set. We fitted the data using two models: Linear regression model and Nonlinear modeling (Neuro network).

**Linear modeling**

The linear model was assumed to be

$P = \beta_1 * x_1 + \beta_2 * x_2 + \beta_3 * x_3 + \beta_4 * x_4 + \beta_5 * x_5 + \beta_6 * x_6$ , where P is the total profit of the six factors, $\beta_i$ is the marginal profit coefficient, and $x_i$ is the marginal profit of the six cost factors. Using MATLAB command mvergress, $\beta$ was found to be:

| $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_4$ | $\beta_5$ | $\beta_6$ |
|---|---|---|---|---|---|
| -3.9 | 5.3 | 10.1 | 7.3 | -5.6 | -2.7 |

Table 2.1: Summary of the beta values of the six factors

As the result tells, the most positive $\beta$ is the Raw material factor. We can interpret that the more expensive Raw material we use, the better marginal profit we will generate from the assembly line. The most negative $\beta$ is the Building factor. We can interpret that the less we spend on building, the more marginal profit we will generate.

**Non-linear modeling**

We used MATLAB command "nnstart" to fit a neural network to the marginal profit data.

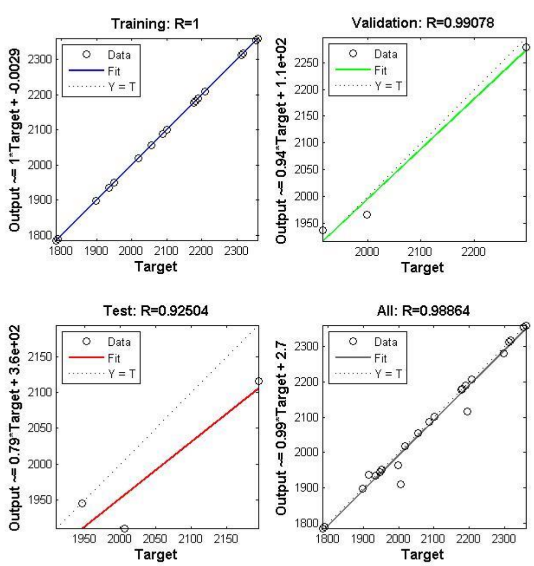


Fig. 2.1: Nonlinear fitting of the data from Neural network.

Neuro network fits the data with a $R^2 \approx 0.977$, which is considered a good fit of the data. The net function generated by the Neural work was the saved, and used to predict new marginal profit based on our changes.

**Result**

Since the model is non-linear, and discrete, we referred to the average cost breakdown in the automotive field. We wanted to find the optimized profit followed the direction of the linear model. After tried different configurations of the cost of the six factors, we came up with optimized costs of the six factors shown in the following table. We have a new profit \$451 per chassis based on the new configuration.

| Cost Factor | Investment (USD/Chassis) |
|---|---|
| Shipping/Receiving cost | 75 |
| Inspection and Testing cost: | 125 |
| Material cost: | 1016 |
| Maintenance cost: | 225 |
| Building cost: | 180 |
| Energy cost: | 150 |

Table. 2.2: Summary of the optimized configuration

## Subsystem 3-Line reconfiguration

**Introduction**

The assembly line is supposed to manufacture different kinds of car chassis since the company has to meet the fluctuating customer demand. There is no such a company that only produces one type of product can survive from the market competition. Therefore, making switches between different types of chassis is necessary for assembly line. The ability to change over to produce a new product, within the defined parts spectrum, economically and quickly is called product flexibility [4]. It is known that changing a line would cost a lot of money because of machine changing, worker training and line stop. Reducing all costs is often viewed as the way to increase product flexibility. In this subsystem, we not only consider the pure cost, but also take the side benefits into consideration. Side benefit includes advertisement effectiveness and company's reputation in this subsystem. Every time the line can produce a new product after switching, it would definitely influence the side benefits of the company because the switching means the company is willing to change to meet the social trend, which would convince the partner and customer and increase their reputation. The main benefits of a good corporate reputation can be found in:

a. Customer preference in doing business with you when other companies' products and services are available at a similar cost and quality;
b. Your ability to charge a premium for products and services;
c. Stakeholder support for your organization in times of controversy;
d. Your organization's value in the financial marketplace [5].

Based on the statement we made above, the whole subsystem is trying to maximum the side benefit that comes from making new types of chassis, while reducing the switching cost.

**Assumption**

- Time span is one year.
- When switches happen, the line has to stop.
- Factory still has to pay for union when line is stopped.
- The changing cost for each machine when switches happen is the same.

**Formulation**

The objective of this subsystem is trying to minimum switch cost including three Parts (Time Span is 1 year):

- f(1) labor cost when switch happens
- f(2) Initial machine cost and machine change cost
- f(3) Side benefits when switch happens

$$minf = f(1) + f(2) - f(3)$$

$$f(1) = x_1 * a * b * \left(\frac{x_2}{1 + x_2}\right) * c$$

$$f(2) = k1 * \left(\frac{1}{1 + x_2}\right) * c * \ln(x_1 + 1) + \frac{k2}{x_2}$$

$$f(3) = neural(x_1)$$

$$data\ driven\ (created\ by\ neural\ network)$$

Subject to:

$$-x_1 \leq 1$$

$$x_1 \leq \frac{365}{a} - k_3$$

$$-x_2 - 0.1 \leq 0$$

$$x_2 - 10 \leq 0$$

Variable:

$x_1 = number\ of\ swithes\ in\ one\ year$

$x_2 = ratio\ of\ human\ work\ over\ machine\ work$

Parameter:

$a = idle\ time\ (days/switch)$

$b = cost\ of\ labor\ benefits\ (dollar/(day * unit))$

$c = total\ work\ load(unit)$

$k1 = cost\ of\ machine\ change(dollar/unit)$

$k2 = cost\ of\ automation\ level\ change$

$k3 = least\ working\ period\ between\ switches$

Constraints:

- Number of switches should be larger than or equal to 1.
- Number of switches should have an upper bound.
- Part of total work should be done by human labor.
- Part of total work should be done by machine.

**Result**

We collected data from a Chinese chassis company about how much switches they have in each year that would influence their side benefits (in dollar). And using neural network fit a nonlinear model regarding to it.

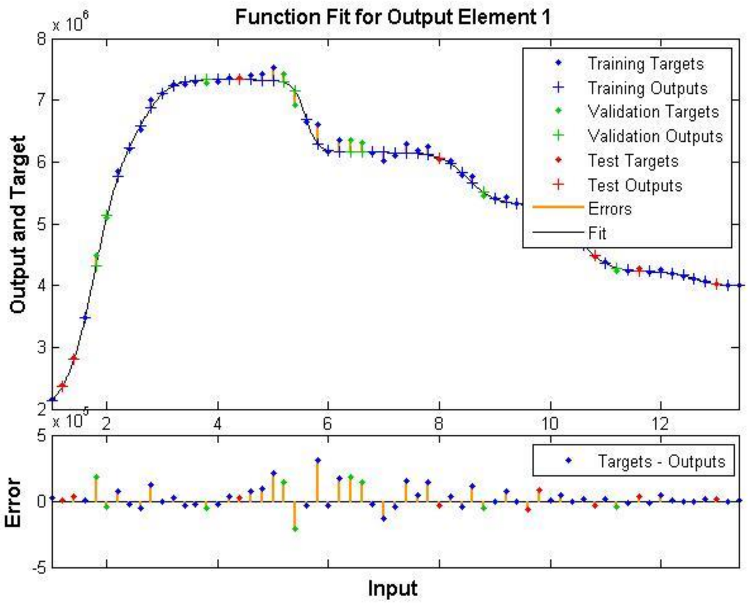


Fig. 3.1: Function Fit

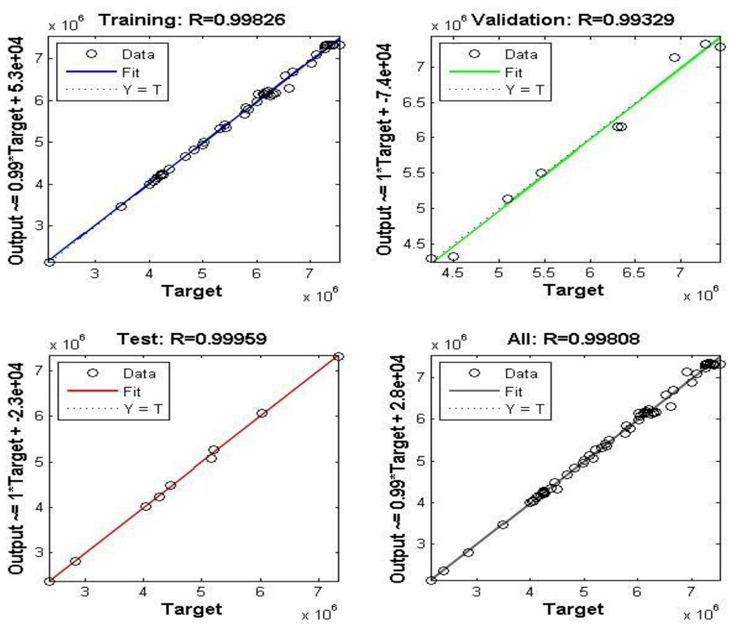


Fig. 3.2: Regression Fit

For this specific company, the parameter is:

| $a$ | $b$ | $c$ | $k_1$ | $k_2$ | $k_3$ |
|---|---|---|---|---|---|
| 11500 | 5 | 9 | 20000 | 200000 | 45 |

Table 3.1: Summary of the parameters

Optimal point:

| $x_1$ | $x_2$ |
|---|---|
| 3.4028 | 0.6917 |

Table 3.2: Summary of the optimal point.

**Optimal Area Analysis**

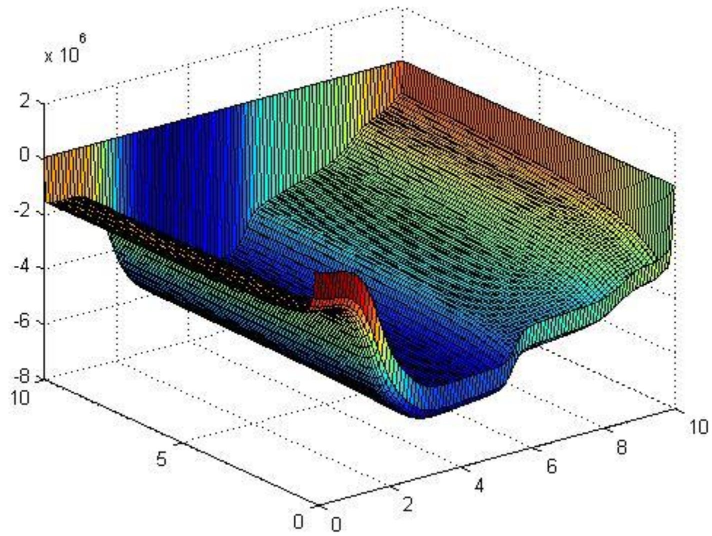


Fig. 3.3: Plot of the optimal area analysis

From the graph above, we can see x(1) – number of switches in one year is much more sensitive to the function, while x(2) – ratio of human over machine is not that sensitive. As a result, the number of shift would influence more on this subsystem.

## Subsystem 4 – Minimize cost of waste

### Introduction

Subsystem 4 deals with the cost of waste. As no manufacturing system can reach 100% system reliability, there will be failed manufacturing parts exists during production. As no reprocessing or recycling of the failed parts is conducted, the cost of waste is calculated as the sum of the material cost and processing cost of the failed parts. The objective of this subsystem is to find the optimal production rate and system automation level to minimize the cost of waste.

**Modeling**

The overall concept formula is shown as:

$$\min Cost\ of\ waste = Amount\ of\ failed\ part\ X\ (Material\ Cost + Processing\ Cost) \qquad Eq.4.1$$

The amount of failed parts is considered as a function of system production rate (variable H) and system reliability. Follow the reliability theory, the amount of failed parts can be simply represented by equation:

$$Number\ of\ fialed\ parts = Production\ rate(h) \times \frac{(1 - Reliability)}{Reliability} \qquad Eq.4.2$$

In equation.2, the system reliability is determined as a function of the automation level of the system. As can be predicted, a highly automated system which has most of the work done by machine must have relatively high system reliability. Here, by setting up the second variable to be distributed human workload over machine workload ratio (variable X), the system reliability forms certain relationship with the variable shown in the figure below. As shown in the figure, the larger the value X is (lower automation level), the less reliable the system is. Based on the existing trend and basic parameters, the system reliability is calculated as:

$$Reliability = 0.75 + 0.1e^{-0.3x} \qquad Eq.4.3$$

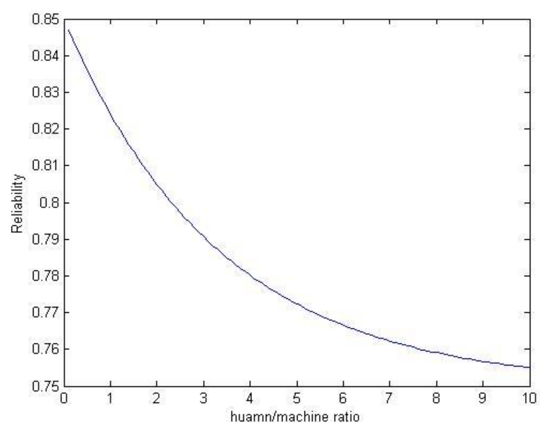


Fig 4.1 Relationship of system reliability over human/machine ratio

Back to the general formulation, the material cost of the failed parts is set as constant for each type of the chassis. The specific value of material cost for individual type is generalized based on results of subsystem 2. The processing cost is considered also a function of the system automation level. As can be inferred, a manually made product may have relatively low processing cost in compare to a machine based product. In other word, the higher the automation level is, the higher the processing cost will be. Based on the existing data of the product, the processing cost equation is set up as:

$$Processing\ cost\ = 80 - \frac{20x}{x + 0.1} \qquad Eq. 4.4$$

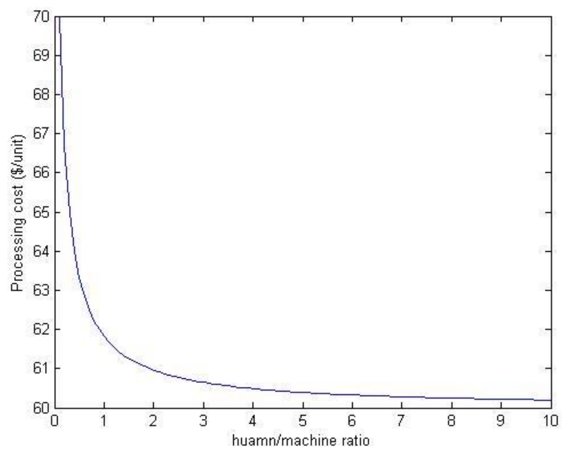


Fig 4.2 Relationship of processing cost over human/machine ratio

After setting the design variables, it is essential to set constrains to the subsystem. As can be imaged, if no product is going to be produced, there will be no failed parts as well as

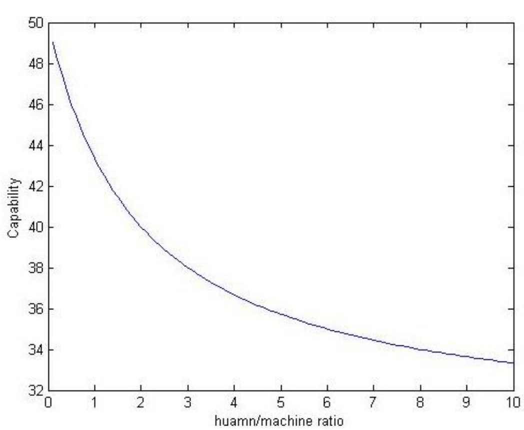


Fig 4.3 Relationship of capacity over X

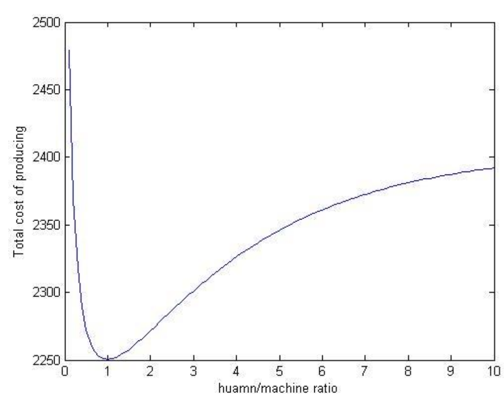


Fig 4.4 Relationship of Cost of waste over X (H)

cost of waste. Thus, constraint is set to the production rate. The way to set up suck constraint is that we limit the production to be greater than the 80% of the system production capability and less than the 100% capability. Such constraint is reasonable because a company will never invest much money to construct a highly automated manufacturing line that can have a maximum production rate of 100 units per day but use it to produce only 10 parts per day. The relationship between the system production capabilities with the variable X is shown in the figure 4.3 below

Figure 4.4 shows the general relationship of the cost of waste over X when the variable of production rate is set as a constant. It can be noticed from the figure that the global minimum exists. Therefore, substitute all the equation into Eq.1 and construct the constraint based on the assumptions, the math formula is show below:

Variable:

$$H: Production\ Rate; \quad x: Human\ Workload/Machine\ Workload$$

**Formula:**

$$\min \quad \sum_i \frac{H}{0.75 + 0.1e^{-0.3x}} * (1 - (0.75 + 0.1e^{-0.3x})) * (1016 + 80 - \frac{20x}{x + 0.1}) \qquad i = 1; 2; 3$$

$$s.t. \qquad g1: \quad H - 0.8(\frac{30x + 100}{x + 2}) < 0$$

$$g2: \quad -H + (\frac{30x + 100}{x + 2}) < 0$$

$$g3: \quad -x < 0$$

$$g4: \quad x < 10$$

**Methods and Results**

Since the analytic model have nonlinear constraint, the SQP method is applied to find the optimum and fmincon strategy using different algorithm is applied to verify the results.

Following the SQP method, the gradient of the objective function and the gradient of the constraint is calculated. The detailed results are shown in the table.

| Method | SQP | fmincon ('sqp') | fmincon('interior-point ') | fmincon('active set') |
|---|---|---|---|---|
| Active Constraint | G1 | G1;G3 | G1 | G1 |
| Iterations | 8 | 4 | 22 | 14 |
| Lagrange Multiplier | 193.7481 | 344.1 ;0 ; 2.5474 ; 0 | 193.7481 | 193.7481 |
| **Optimal H** | **39.1283** | **26.6667** | **39.1283** | **39.1283** |
| **Optimal x** | **0.1152** | **10** | **0.1152** | **0.1152** |

Table 4.1 Optimization results using different algorithm

From the table above, the SQP method yields the results that with production rate of 39.1283 units/day and 0.1152 human/machine ratio, the system will have minimum cost of waste. One interesting thing is that when using fmincon to verify the results, 'sqp' algorithm will yield different results to the traditional SQP method. Fmincon's 'sqp' method has two active constraints while the 'interior-point' and 'active-set' algorithm both share the results with the traditional SQP method. Based on the understanding, the optimal H = 39.1283 is considered as the optimum since the final value of the general function at certain point is smaller than the optimal point get by fmincon's sqp method. The detailed results are attached in APPENDIX.

Since we find out that the processing cost is quite small in comparison with the material cost. The impact of changing the material cost is analyzed based on same model. Given six different fixed material cost, the optimal behavior is shown in the table below.

| | Optimal H and x | |
|---|---|---|
| Material cost | H | X |
| 850 | 39.0193 | 0.1306 |
| 900 | 39.0581 | 0.1251 |
| 950 | 39.0944 | 0.1200 |
| 1000 | 39.1283 | 0.1152 |
| 1050 | 39.1601 | 0.1108 |
| 1100 | 39.1900 | 0.1066 |

Table 4.2 Optimization results using different material cost

From the table, it can be conclude that the material cost have slightly impact on the optimal point of the general formula. If the material cost increases, higher automated system is suggested to lower the cost of waste. This is reasonable since the more material cost is dominate the cost of waste, the better system should be used to optimize the production rate.

The results coming from this subsystem will trade-off with both subsystem 1 and subsystem3, since cost of waste share variable H (production rate) with subsystem 1 and variable x (human/machine ratio) with subsystem 4. The general formula for this subsystem will also be directly put into the overall system level profit analysis to find the global optimal condition.

## System level optimization

For system level optimization, the four subsystem trade-off with each other by sharing variables. As introduced in the introduction section, the overall system formula is:

$$\max \quad System\ Profit = Optimized\ Production\ Rate\ \times Marginal\ unit\ Profit - Cost\ of\ Reconfiguration - Cost\ of\ Waste$$

Taken all the four subsystem into consideration, several variables in each individual subsystem is settled down as a parameter in the overall system. The only two variables left to be optimized are production rate (H) and system automation lever (human/machine x). The table below listed the settled variables as well as the undetermined variable exists in the individual subsystems.

| | Type A | Type B | Type C | System |
|---|---|---|---|---|
| Producing Time interval [days] | 53 | 57 | 53 | |
| Marginal Profit [$/unit] | 450 | 470 | 510 | |
| Number of switch in an year [times] | | | | 3 |
| Material cost [$/unit] | | | | 1016 |
| **Production rate** | **H1** | **H2** | **H3** | |
| **Relative system automation level** | **X1** | **X2** | **X3** | |

Table 5.1. List of settled variable and variables need to be optimized

In system-level analysis, the formula of subsystem 3 (Cost of Reconfiguration) and subsystem 4 (Cost of Waste) can be directly applied into the general formula as the unit of them is $. The production rate (subsystem 1) need to be multiply by the marginal profit of individual product (subsystem 2) to get the overall profit of the system. To do so, the formula of subsystem 1 need to be modified based on the concept figure shown below.

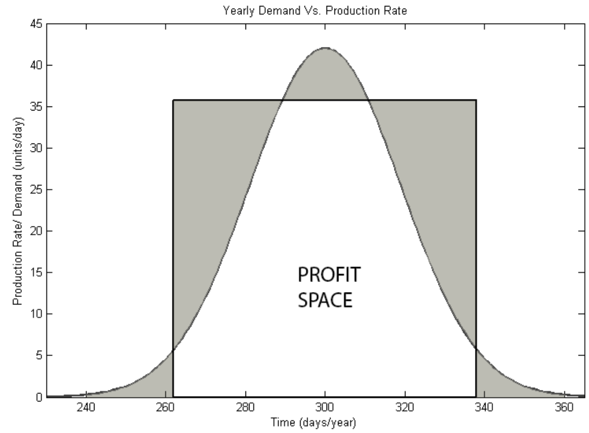


Fig 5.1. Plot of profit space concept.

As shown by the figure, the shaded area are either over produced or unachieved demands. So the profit are is the amount of product that make net profit. Thus, the profit area is calculated as:

$$\int_{starting\ time}^{ending\ time} (Production\ rate - Demand)$$

Now, substitute all the subsystem formula into the overall equation, the overall optimization formula is:

$$max \quad System\ Profit = \sum_i \int_{starting\ time}^{ending\ time} (Production\ rate - Demand) \times Marginal\ unit\ Profit - Cost\ of\ Reconfiguration - Cost\ of\ Waste$$

1) $Production\ rate = H_i;$
$Demand = C_i \times normpdf(t, \mu_{0_i}, \sigma_i);$
$C_i = 2000; 3000; 2500\ for\ product\ A, B, C$

2) $Marginal\ unit\ Profit = 450(M_1); 470(M_2); 510(M_3);$

3) $Cost\ of\ Reconfiguration = 3 \times 43000 * \left(\frac{x}{1+x}\right) + 180000 * \frac{1}{1+x} * \ln(4) + \frac{200000}{x} - net(3);$
$net(3) =$
$Data\ driven\ model\ of\ subsystem\ 3\ with\ number\ of\ switch\ equals\ to\ 3$

4) $Cost\ of\ Waste = \sum_i \frac{H_i}{0.75+0.1e^{-0.3x}} * (1 - (0.75 + 0.1e^{-0.3x})) * (1016 + 80 - \frac{20x}{x+0.1})$

$s.t.$

$$g1: \quad H - 0.8\left(\frac{30x + 100}{x + 2}\right) < 0$$

$$g2: \quad -H + \left(\frac{30x + 100}{x + 2}\right) < 0$$

$$g3: \quad -x < 0$$

$$g4: \quad x < 10$$

Apply fmincon strategy, the system optimized results is shown in the table below.

| | Optimal H [units/day] | Optimal X [ratio] | Active Constraint | F value [$/year] |
|---|---|---|---|---|
| Type A | 35.4273 | 0.8003 | G1 | -4.9874e6 |
| Type B | 45.4809 | 0.5838 | G2 | -4.1359e6 |
| Type C | 41.6570 | 0.6583 | - | -4.5270e6 |
| Total | | | | -13.6503e6 |

Table 5.2. Optimization results of the overall function.

The table shows the exact optimized value of individual type of product, analyzing the active constrain we can conclude that product A is limited by the least production capability constrain which means product A gain relatively little profit with the growth of system automation level. In comparison, product B is constrained by 100% production capability which indicates that B can get great profit at certain automation level so that it should be produced at a maximum production rate. Type C has no active constraint which means that the two variable trade-off well and the local minimum for the cost is found. Overall, the optimized system can generate a profit of $ 13,650,300 per year.

## CONCLUSION AND FUTURE WORK

The objective of the project is to determine automation level to maximize the profit of a chassis manufacturing company located in company. After running a system level optimization, we had a profit of $ 13,650,300 per year, with an automation level of 0.8003, 0.5838, and 0.6583. And a production rate of 35.4273, 45.4809, and 41.6570 units/day.

As of future work, the optimization was only for one manufacturing line, and a multi-line factory would be more realistic. Moreover, we would like to collect more detailed data about the performance of a real chassis manufacturing line. And for the next step, we had the targeted composition of the line, and we wanted to look into what we can change of the assembly line in the technical side to achieve the goal.

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# APPENDIX

a. MATLAB codes for Subsystem 1.

Subsystem 1 Production Rate Optimization

```
%% objective function
function y = myfnction(x)

  t = 1:0.01:365;
  a = 200-x(2)/2;
  b = 200+x(2)/2;
  ha = cumulative(a);
  hb = cumulative(b);
  d = (3500/((sqrt(2*pi))*20))*exp(-((t-200).^2)/(2*20^2));
  p = x(1)*(ha-hb);


  err = (d-p).^2;
  errlnteg = 0;
  for i = 1:length(err)
  errlnteg = errlnteg+err(i)*0.1;
  end
  y = errlnteg;
end

%% car-box function define
function cumu = cumulative(x)
t = 1:0.01:365;
k = 1000;
cumu = 1-exp(-(t/x).^k);
end

%% fmincon algorithm
clear;clc;
A = [];
B = [];
Aeq = [];
Beq = [];
lb = [0;0];
ub = [40;300];
x0 =[20;10]; %initial value
% notice H=x(1);T=x(2);
[x,fval] = fmincon(@myfnction,x0,A,B,Aeq,Beq,lb,ub);

%% Visual Optimization Results
clear;clc;
syms x
```

```
%%
%************demand parameter setting*************%
MU_1 = 100;
MU_2 = 200;
MU_3 = 300;
SIGMA_1 = 10;
SIGMA_2 = 19;
SIGMA_3 = 19;
Demand_Weight_1 = 2000;
Demand_Weight_2 = 3000;
Demand_Weight_3 = 2500;
%%
%************rectangle parameter setting************%
% input data is based on the fmincon results or mathematica results
x1 = MU_1 - 3*SIGMA_1;%based on 2-sigma
x2 = MU_2 - 2*SIGMA_2;
x3 = MU_3 - 2*SIGMA_3;
w1 = 2*(MU_1 - x1);
w2 = 2*(MU_2 - x2);
w3 = 2*(MU_3 - x3);
h1 = 0.85*Demand_Weight_1/(SIGMA_1*sqrt(2*pi));
h2 = 0.85*Demand_Weight_2/(SIGMA_2*sqrt(2*pi));
h3 = 0.85*Demand_Weight_3/(SIGMA_3*sqrt(2*pi));
%%
%************demand and production rate************%
x = 1:1:365;
A = Demand_Weight_1*normpdf(x,MU_1,SIGMA_1);
rectangle('position',[x1,0,w1,h1],'curvature',[0,0])
plot(x,A,'b')
hold on
B = Demand_Weight_2*normpdf(x,MU_2,SIGMA_2);
rectangle('position',[x2,0,w2,h2],'curvature',[0,0])
plot(x,B,'r')
hold on
C = Demand_Weight_3*normpdf(x,MU_3,SIGMA_3);
plot(x,C,'g')
rectangle('position',[x3,0,w3,h3],'curvature',[0,0],'LineWidth',2)
hold on
M = A+B+C;
plot(x,M,'or')
```

b. Subsystem 3

Subsystem 3 matlab

Solution.m

```
% Fmincon solution
x0 = [1;1];
A = [-1,0;1,0;0,1;0,-1]; b=[0;67;7/2;-1/8]; Aeq=[]; Beq=[]; lb=[]; ub=[];
options = optimoptions('fmincon','GradObj','on');
x = fmincon('obj',x0,A,b,Aeq,Beq,lb,ub);
x_test = [4;3.5];
t = obj(x_test);
load('y2.mat');
```

```
%Objective Function
```

Obj.m

```
function f=obj(x)
   load('net.mat');
   f = x(1)*430000*(x(2)/(1+x(2)))+180000*1/(1+x(2))*log(x(1)+1)+200000/x(2)-
net(x(1));
end
```

c. Subsystem 4

```
A = [];
B = [];
Aeq = [];
Beq = [];
lb = [];
ub = [];
x0 =[30 0.2];

% options = optimoptions(@fmincon,'Algorithm','active-set','MaxIter',1500)
options = optimoptions(@fmincon,'Algorithm','interior-point','MaxIter',1500)
% options = optimoptions(@fmincon,'Algorithm','sqp','MaxIter',1500)
% [x,fval,exitflag,output,lambda,grad,hessian] =
fmincon(@costofwaste,x0,A,B,Aeq,Beq,lb,ub,@confun);
[x,fval,exitflag,output,lambda,grad,hessian]=fmincon(@costofwaste,x0,A,B,Aeq,Beq,l
b,ub,@confun,options);

function y = costofwaste(x)

 P0 = 80;
 P1 = 20;
 P2 = 0.1;
 MC = 1100;


 R = 0.75+0.1*exp(-0.3*x(2));
 k = R/(1-R);

 PC = P0 - P1*x(2)/(x(2)+P2);


 y = x(1)/R*(1-R)*(MC+PC);

end
```

d. Overall system

```
A = [];
B = [];
Aeq = [];
Beq = [];
lb = [];
ub = [];
x0 =[30 0.2];

options = optimoptions(@fmincon,'Algorithm','active-set','MaxIter',1500)
% options = optimoptions(@fmincon,'Algorithm','interior-point','MaxIter',1500)
% options = optimoptions(@fmincon,'Algorithm','sqp','MaxIter',1500)
% [x,fval,exitflag,output,lambda,grad,hessian] =
fmincon(@costofwaste,x0,A,B,Aeq,Beq,lb,ub,@confun);
[x,fval,exitflag,output,lambda,grad,hessian]=fmincon(@myfnction,x0,A,B,Aeq,Beq,lb,
ub,@confun,options);

function y = myfnction(x)

%% Production Rate Optimization/ PF = Production Profit
  Ci = 3000; %2000,3000,2500 [units]
  ti = 200;  %100,200,300 [specific day]
  Mi = 470;  %450,470,510 [$/unit]
  PT = 57;   %53, 57, 53 [days]
  t = 1:0.01:365;
  a = ti-PT/2;
  b = ti+PT/2;
  ha = cumulative(a);
  hb = cumulative(b);
  d = (Ci/((sqrt(2*pi))*19))*exp(-((t-ti).^2)/(2*19^2));
  p = x(1)*(ha-hb);


  err = abs(d-p);
  errlnteg = 0;
  for i = 1:length(err)
  errlnteg = errlnteg+err(i)*0.1;
  end

  PF = (2000+x(1)*PT-errlnteg)/2;

 %% Cost of Waste
 P0 = 80;
 P1 = 20;
 P2 = 0.1;
 MC = 1016;
```

```
R = 0.75+0.1*exp(-0.3*x(2));
k = R/(1-R);

PC = P0 - P1*x(2)/(x(2)+P2);


COW = x(1)/R*(1-R)*(MC+PC);

%% Cost of Reconfiguration
load('net.mat');
COR = 3*430000*(x(2)/(1+x(2)))+180000*1/(1+x(2))*log(3+1)+200000/x(2)-
net(3);

%% Overall Formula
y = COW*PT-PF*Mi+COR;
end

function [c,ceq] = confun(x)
cap = (30*x(2)+100)/(x(2)+2);
c = [-x(1)+0.8*cap;x(1)-cap;-x(2);x(2)-10];
ceq=[];
end

function cumu = cumulative(x)
t = 1:0.01:365;
k = 1000;
cumu = 1-exp(-(t/x).^k);
end
```