Design Characteristics Optimization of Flexible-Automated Manufacturing System

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ABSTRACT

Decision of how to change design characteristics of flexible-automated system in terms of production processes effective time is a sensitive decision for a manufacturer. The sensitivity is related to the system running stability and the decision needs to be as how best to expand will have a lasting impression, with the potential for huge gain or loss of the produced units. A real-world manufacturer in the automotive industry is capable to manufacturer of three products: P1, P2, and P3. The first two currently is produced on a BIW system working at maximum capacity. The company needs to expand its production and is looking for the best alternative that will support its growing needs and serve it well in the future. This research provides a decision making model for whether the design is best to increase the capacity of the current BIW line or build a second line to have dedicated production of P1 and P2. A discrete-base modeling approach has been used to create an optimizable model for the system to empirically apply the solutions. Rockwell ARENA 14.7 software and MINITAB 16 software are used to simulate the model, experiment, and gather results the two scenarios investigating capacity requirements for the most cost effective expansion.

2. INTRODUCTION

This applied research aims to determine the total throughput and capacity breakeven point at which an expansion of the system's current combined P1 and P2 compares to the alternative of adding a second line so that each line can make a dedicated product. Under the current manufacturing process, which is not altered in this research, P1 is an input part for the creation of P2 which serves as an input for the final product P3. Decision making is trying to determine the most cost-effective scenario for expansion to ultimately produce more P3. ARENA is used to simulate the two models of manufacturing circumstances to determine capacity requirements for the most cost-effective one of expansion. The processing steps for the manufacturing of the products are not to be examined; the process remains in its current arrangement. Only the capacity of the current line and the new design of two lines are to be investigated. Firstly, the current manufacturing line is modeled to be as a baseline for comparison. This model is validated to meet the current output specification of the existing line. In the first set of model iteration, the current manufacturing line has been expanded to meet the desired process output increase of P1 and P2; which is considered the first alternative. The most time consuming process steps are examined first to determine if localized process expansion can sufficiently increase product output; if not sufficient further element expansions are to be made until the output increase meets requirements. The second set of iterations is to model a second parallel line for the production of P2. The existing manufacturing line will remain in place and only produce P1; which is the second alternative. Under this layout, one of the processes the cleaning process can be eliminated from each line for the technical reason of a full system flush and clean is not required as each line now has a single dedicated product. Simulation is the technique of developing a model of a real system which can be utilized to examine the behavior of the system under certain conditions [3]. Particularly, simulation provides important advantages to investigate the behavior of a system which do not yet exist to transfer the findings into reality, as well as the performance of a real or existing system without directly intervening current operations [2, 7]. Discrete event simulation (DES) is one of the most commonly used tools especially in the area of production planning and control. DES is appropriate for modeling and analyzing material flows, resource utilization, and logistic processes of manufacturing systems [1]. In manufacturing, DES is a significant tool that can be used to analyze the efficiency via the consideration of what-if scenarios, conclusions can be drawn on how to optimize a system's performance before its construction or use [4]. The factory layout including its entire elements, such as machines, transport units, and warehouses, either as single entities or combined into production lines can be mapped by DES [8]. Medical product developers, government agencies, education and research institutions, as well as health institutions have recognized the substantial potential of computational modeling and simulation (M&S) to support clinical research and decision making in healthcare, e.g., [6]. Thus, research activities in computational medicine are growing at a significant rate and remarkable discoveries are being made [5].

The objective of this research is to highlight what increases in line capacity are needed and where the increased capacity needs to go in a single, dual product line design. Inversely the models will highlight the required capacity of a second dedicated manufacturing line for one of the products. The results can then be used by the decision making to determine the most cost-effective expansions for the plant. Section 2 is devoted to the related research works reviewing; section 3 is to analyze the collected data and description the variables of the model; section 4 describes the phases of the model creating and the major assumptions; section 5 has been devoted for the experimenting the alternatives preparing to the analysis; and section 6 is to analyze the research results and investigating the optimal solutions.

3. LITERATURE REVIEW

Loo, L. et al. [9] provide a framework for simulation models that use innovation in the systems modeling. The research paper focuses on how innovations in simulation models of complex systems need a framework. Because the industry presents unique challenges as well as opportunities in modeling complex systems in innovative ways, therefore the simulation has many effects on the overall model and can be a useful tool. The results show that the innovative framework used proves the system modeling technique. Sadoun, B. [10] provides an in-depth look into the processes behind applying system simulations. He also applies the analytical knowledge outlined as methodology to an applied case study. An extensive tutorial on how to conduct an experiment using simulation was written by Barton, R. [11]. Grimard, C. et al. [12] redesigned an existing cell in a plant, and used simulation to validate the cell. They also discussed why the designed throughput could not be achieved, with the help of their simulation. Similar methods were applied to a construction problem. Another research used modeling and a design of experiments to address the issue of insufficient resource levels. There paper directly looks at an example in pouring concrete Zahraee, S. et al. [13]. Another set of authors researched the optimal input order for a job shop system that had flexible inputs. The goal was to optimize the production schedule and improve the slack in the system. Their system provides the optimal given a set of values for certain variables Cheng, H. and Chan, D. [14]. Optimization through simulation has also been applied to the supply chain field. Chu, Y. and You, F. [15] developed a simulation to help optimize the network for supply distribution.

4. INPUT DATA ANALYSIS

The data was collected from real-world system of P1, P2, and P3. The system supplies these products to one of the top research-based automotive companies in the United States. The automotive company uses the final product produced by the system, P3 to produce the products which are distributed and sold around the world. The system manufacturing processes are computer controlled and constantly monitored by the system. The data for this study was automatically collected by the computer control software. The records from the past year were pulled from the computer archive for the time of each process, the amount of materials added to each batch, the reaction/ processing time for each step in the manufacturing process, and annual throughput. The data used in this study is based on one year of continuous process run time. The system is continuous running 24 hours a day 7 days a week. For this reason all full line simulation will be run for one continuous year or 8700 hours. For every 720 hours (roughly one month) there are 8 hours of downtime for preventative maintenance, this will be accounted for in all simulations using a failure process to imitate the down time at which time the line will pause. To mirror the actual manufacturing process as closely as possible the start time from manufacture of P1 and P2 are set off by the completion of the other. Therefore, P2 only begins to be manufactured once an entire P1 process has run from beginning to end. The final assumption is that the data provided by the system does mirror the actual manufacturing process.

As a result of employer confidentiality, the raw production data could not be shared, only a data summary was shared. The data provided was said to have been run through a process similar to ARENA's Input Analyzer function to create the process time distributions provided for this study. As mentioned the provided data is a summary of one year of continuous production of P1 and P2. Additionally, only a summary of the process times were shared as a result of confidentiality agreements, see **Error! Reference source not found.** for all reaction and process time data. All times are given in hours. The throughput of the plant was 160 batches each of P1 and P2 for the given time period.

Table 1: Process Time Distributions (hrs)

P1		**P2**	
Process	**Description**	**Process**	**Description**
Mixing	TRIA(10,12,14)	Mixing	TRIA(11,13,15)
Heating	TRIA(1,3,5)	Heating	TRIA(4,6,8)
Cooling	TRIA(1,2,3)	Cooling	TRIA(2,4,6)
Drying	TRIA(1,3,5)	Drying	TRIA(4,6,8)
Packaging	EXPO(1)	Packaging	EXPO(1)
Cleaning	EXPO(2)	Cleaning	EXPO(2)

5. SIMULATION MODEL BUILDING-UP

After analyzing the time study data, a discrete event simulation model was developed that will run for 8700 hours. The model begins with a create module that produces one single arrival at the beginning of the simulation. The created entity then goes through an assign module that allocates the attribute type of the entity as TYPE 1 which corresponds to P1. This attribute assignment is used to assign the processing time data required for HPA as it moves through the 6 processing stations. The processing times are defined under expression in ARENA in a 2 x 6 matrix, see Figure 1, where attribute TYPE 1 represents the first row and each column represents one of the manufacturing processes. The second row is designated for TYPE 2 which is P2 and will be assigned later. After the first batch completely runs through the 6 processes it runs through an assign variable which uses a boolean string "(TYPE==1)*2 + (TYPE==2)*1." This string changes the attribute type from 1 to 2 or 2 to 1 depending on the incoming batch. The reason for this is the creation of P2 relies on the production of P1. Therefore, the model is setup to run in a loop, alternating which product is produced each time. After the assign module the product then runs through a separate module. The original out of the separate is counted and statistics are recordered. The other output runs through a decide module and through a set of assign processes to change the attribute picture. After the reassignment is completely done the entity goes straight to the first processing station, mixing. This process continues, switching between P1 (TYPE 1) and P2 (TYPE 2) for the full production time. The only time that the line stops is for 8 hours of preventative maintenance every 720 hours of operation in which case the entire system pauses. The single dual-product line is shown in Figure 2.

	1	2	3	4	5	6
1	TRIA(10, 12, 14)	TRIA(1, 3, 5)	TRIA(1, 2, 3)	TRIA(1, 3, 5)	EXPO (1)	EXPO (2)
2	TRIA(11, 13, 15)	TRIA(4, 6, 8)	TRIA(2, 4, 6)	TRIA(4, 6, 8)	EXPO (1)	EXPO (2)

Figure 1: Time Matrix in ARENA Expression Values

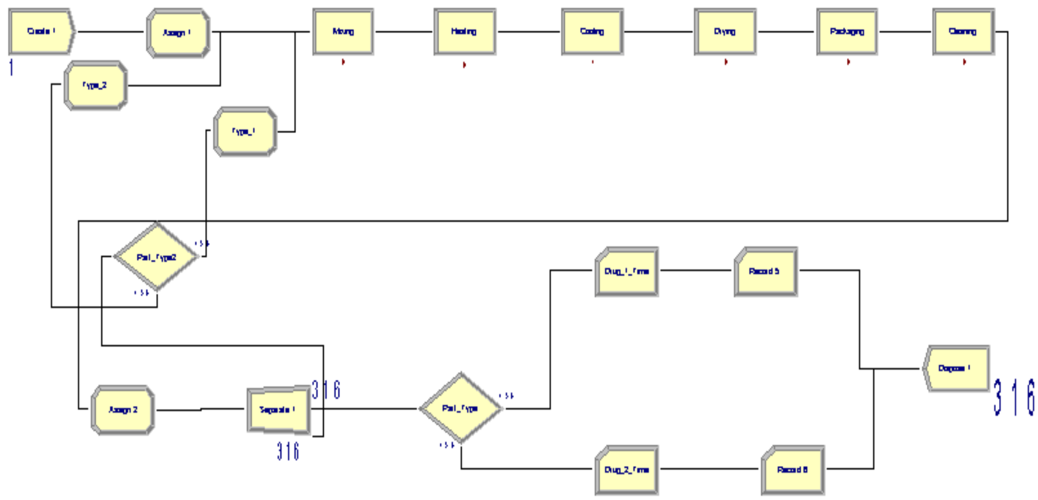

Figure 2: Original ARENA Simulation, Single Dual-Product Line

6. EXPERIMENTION SETTING-UP

Using design of experiment principles a regression model was built for the data set. The same six processes are followed by each of the two products, the only variation being the time that each requires. A 2^k factorial design of experimentation was created for the 6 processes. Given a full 26 design there would have been 64 runs required to meet the full replication set. To reduce simulation time, a ¼ factorial design was used. This reduced the number of required simulations down to 16 runs. For each process and product a high and low level production time was developed by taking the minimum and maximum process time from the triangular distributions provided by the system to determine the impact of that processing factor on the manufacturing process. See Table 2 below for the high and low levels for each. Figure 3, the design matrices followed by the ¼ factorial designs for all processes and the total throughput that each run yielded.

Table 2: Processing Time Levels for Each Product

Level	**Low (-1)**	**High (+1)**	**Low (-1)**	**High (+1)**
Process	**P1**		**P2**	
Mixing	EXPO (10)	EXPO (14)	EXPO (11)	EXPO (15)
Heating	EXPO (1)	EXPO (5)	EXPO (4)	EXPO (8)
Cooling	EXPO (1)	EXPO (3)	EXPO (2)	EXPO (6)
Drying	EXPO (1)	EXPO (5)	EXPO (4)	EXPO (8)
Packaging	EXPO (1)	EXPO (1)	EXPO (1)	EXPO (1)
Cleaning	EXPO (2)	EXPO (2)	EXPO (2)	EXPO (2)

	StdOrder	RunOrder	CenterPt	Blocks	Mixing	Heating	Cooling	Drying	Packaging	Cleaning	Througput
1	1	1	1	1	-1	-1	-1	-1	-1	-1	431
2	9	2	1	1	-1	-1	-1	1	-1	1	353
3	5	3	1	1	-1	-1	1	-1	1	1	374
4	4	4	1	1	1	1	-1	-1	-1	1	304
5	7	5	1	1	-1	1	1	-1	-1	-1	319
6	2	6	1	1	1	-1	-1	-1	1	-1	354
7	3	7	1	1	-1	1	-1	-1	1	1	362
8	12	8	1	1	1	1	-1	1	-1	-1	266
9	16	9	1	1	1	1	1	1	1	1	243
10	15	10	1	1	-1	1	1	1	-1	1	277
11	8	11	1	1	1	1	1	-1	1	-1	278
12	10	12	1	1	1	-1	-1	1	1	1	300
13	13	13	1	1	-1	-1	1	1	1	-1	311
14	14	14	1	1	1	-1	1	1	-1	-1	272
15	11	15	1	1	-1	1	-1	1	1	-1	303
16	6	16	1	1	1	-1	1	-1	-1	1	313

Figure 3: ¼ Factorial Designs

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Analysis of Variance

Source       DF  Adj SS   Adj MS  F-Value  P-Value
Model         4   33540   8384.9    69.90    0.000
  Linear      4   33540   8384.9    69.90    0.000
    Mixing    1   10000  10000.0    83.36    0.000
    Heating   1    7921   7921.0    66.03    0.000
    Cooling   1    5112   5112.3    42.62    0.000
    Drying    1   10506  10506.3    87.59    0.000
Error        11    1319    120.0
Total        15   34859


Model Summary

      S    R-sq  R-sq(adj)  R-sq(pred)
10.9524  96.21%     94.84%      91.99%


Coded Coefficients

Term       Effect    Coef  SE Coef  T-Value  P-Value   VIF
Constant           316.25     2.74   115.50    0.000
Mixing     -50.00  -25.00     2.74    -9.13    0.000  1.00
Heating    -44.50  -22.25     2.74    -8.13    0.000  1.00
Cooling    -35.75  -17.88     2.74    -6.53    0.000  1.00
Drying     -51.25  -25.63     2.74    -9.36    0.000  1.00


Regression Equation in Uncoded Units

Througput = 316.25 - 25.00 Mixing - 22.25 Heating - 17.88 Cooling - 25.63 Drying
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Figure 4: Analysis of Variance and Regression Equation

It is critical to validate the assumptions of the model. For this a residual analysis will be performed, see Figure 5 for the residual analysis plots. The first assumption is that the probability distribution of the error is normally distributed with a mean of zero. By looking at the normality plot it is evident that this assumption is confirmed. There are no data points that stray significantly from the normal line. The second assumption is of constant variance in the model. This is shown by the versus fit plot. As one can see there is a parabolic pattern in the variance. This would tend to say that there is not constant variation in the model which would be shown if there was no pattern at all to the data fit. The final assumption that needs to be checked is that the error is independent between all variables. This is done using the observation order to ensure that the tests are consistent by seeing if there is a pattern or not in the data. As one can see the discrepancies are in the 1st and 16th observations. These two observations were the culmination of entirely high and low factors in the factorial model which is why they appear to be so far out of place. However, the stability and repeatability of the model is valid. The ARENA platform is able to recreate any of the simulation over and over without change. The error that a physical process would introduce into a model such as this one can be ignored in this case. Independence can be assumed for this model. Upon analysis of this regression model everything seems to be in order with the exception of the constant variance. While this does not definitively invalidate the model it is a point of concern.

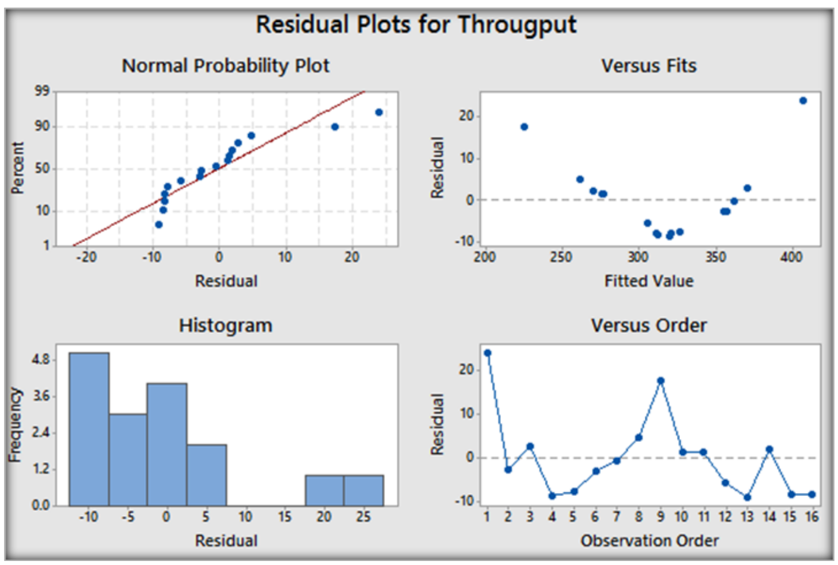

Figure 5: Residual Plots

With this being said, the resulting regression equation is not extremely helpful to the analysis as throughput will always be maximized when the time of each process is minimized. What this analysis does highlight is the impact of the dependent variables on processing time on the throughput of the system (independent variable). This is reiterated by Figure 6 of the Pareto Chart of Standardized Effects showing D (drying) having the greatest impact on throughput.

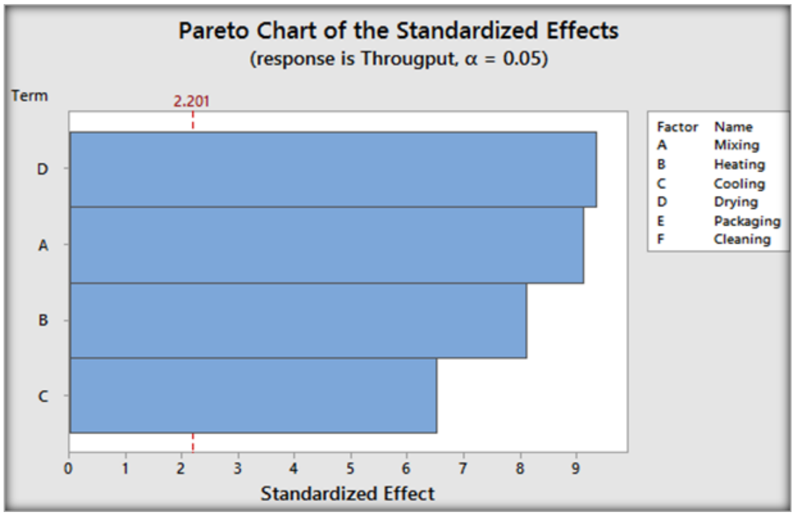

Figure 3: Pareto Chart of Standardized Effects

7. RESULTS ANALYSIS

The utilization of each piece of equipment in the manufacturing process is very low as shown in Table 3. The reasoning for this is that each piece of equipment is sitting idle either waiting to process or after it has finished performing its process on the current batch. By far the largest utilized piece of equipment is the mixing machine at 45.78%. This will be the target of the improvement analysis as it clearly is the bottleneck of the system because of its comparatively ling processing time. If the processing time can be reduced for this machine the total throughput can be increased.

Table 3: Resources Utilization

Resources	Utilization %
Mixing	45.78
Heating	16.21
Cooling	10.89
Drying	16.51
Packaging	3.55
Cleaning	0.64

Given the current process for the manufacturing of P1 and P2 queuing is not an issue. As a result of the batch process that the system runs on, the product never has to wait to proceed to the next station because the machine is sitting idle. There is then a full system delay for cleaning as which point the raw materials for the next product are being prepared for processing. Similarly, there is never more than 1 batch that is in process at any one time and that batch is only ever being processes on a single machine. Additionally, because the process is continuous for an entire year WIP is not an issue with this production process. Throughput is the primary element of this analysis. The system requires 240 batches per year of both P1 and P2 but is currently only at 160 batches of each. Due to the nature of the chemical processes that must take place to result in the drugs being produced correctly, capacity is the variable that must be adjusted. In terms of the simulation model this will be done by changing the processing time but will be reported to management as a capacity increase requirement. Currently the line is out of balance in terms of a balanced processing time on each piece of equipment. The primary difference in this case and why this is not a direct issue is a result of the batch nature of production. All machines but one is sitting idle at any given time as they wait for the machine before them to finish processing. While the time of each piece of equipment contributes to total process time, it is never holding up the rest of the process as one would consider in a traditional case thus requiring line balancing. Comparing the simulation data from the model to the data that was collected by the system, the annual throughput is very close. The system produces 320 total units of P1 and P2 per year (160 each). The model produces 316 total units per year (158 each). Thus the model captures 98.75% of actual throughput. From that information, it was considered that, that is not a significant difference between the simulation and actual plant production.

For the first alternative, the objective is to increase the capacity of the current line while retaining the single production line; dual product layout. To achieve the target combined output of 480, an iterative method was used that adjusted the original processing times supplied by the system with a multiplier for each process. The multiplier represents the required change in capacity that the processing time must experience to get the correct final line output. Table 4 below shows multiple potential time capacity changes with the corresponding output. Based on production time the mixing process was the throughput bottleneck of the system. Therefore, the first objective was to look at that station alone to try and meet the throughput targets. Iteration A from Table 4 shows the multiplier required. The challenge with iteration A, and all of the iterations for that matter, is that not only does the process with the multiplier need to be changed but every other process does as well. The reason for this is if the capacity for mixing is increased all other processes need to be adjusted accordingly to handle the increased throughput. Further iterations and options were conducted to give management a better idea of what can be done to meet the throughput targets. It will be their decision to determine the most cost effective increases to meet the target numbers as none of that data was supplied to this study.

Table 4: Single Line, Dual Product Improvement Iterations

Iteration	**A**	**B**	**C**	**D**
Throughput	479	482	478	480
Mixing	0.26	0.68	0.55	0.62
Heating	1	0.55	0.7	0.62
Cooling	1	0.55	0.7	0.62
Drying	1	0.55	0.7	0..62
Packaging	1	1	1	1
Cleaning	1	1	1	1

The second alternative was to create two parallel production lines that each produce their own product of either P1 or P2. Figure 4 shows the ARENA model of the new process. The overall manufacturing process is the same as the original model with the exception of the cleaning process which has been removed. As a result of the products not switching lines the system does not need a full purge to run the second product.

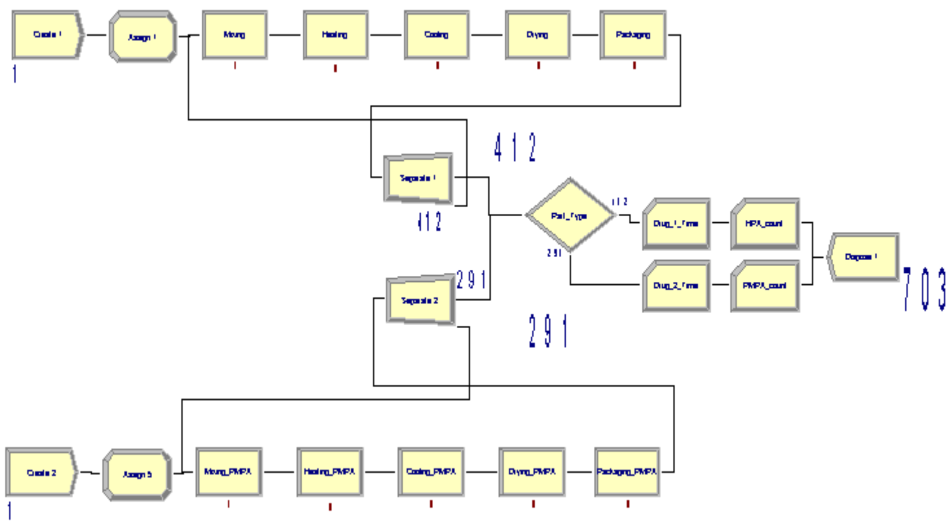

Figure 4: Two Single-Product Lines Process

The initial run for this model was made with the original production capacity of the original line. This would be a scenario where an exact replicate of the existing lines was put in place. With this capacity (multiplier of 1) the throughput far surpasses the system's requirements. In this simulation P1 yields 412 and P2 yields 291 for a total of 703, far exceeding the required value. A similar iterative process was used that adjusted the original processing times to mimic changed capacity to simulate the throughput. The multipliers and throughput results are shown in Table 5. As one can see as a result of the differing production times for each of the drugs the capacity for each line needs to be different. This would require not only a new production line but also a complete overhaul of the existing line in order to not far out exceed the production requirements. In a new two line setup the production time would need to be nearly cut in half for P2 and by nearly two and a half times for P1. There was no further iteration run for this analysis as the capacity change requirements seemed to be over reaching.

Table 5: Dual Line Single Product Iterations

Iteration	**Original**		**New**	
Product	**P1**	**P2**	**P1**	**P3**
Throughput	412	291	162	163
Mixing	1	1	2.65	1.8
Heating	1	1	2.65	1.8
Cooling	1	1	2.65	1.8
Drying	1	1	2.65	1.8
Packaging	1	1	1	1

8. CONCLUSIONS AND RECOMMENDATIONS

Through the efforts of creating a virtual manufacturing simulation model of the system's process for the creation of P1 and P2 several lessons were learned. The first was that a valid simulation model could be constructed from the given data that mirrors the output observed by the existing the system process. The second was by changing the capacity alone but not the steps in the manufacturing process the desired increased output could be achieved. After a thorough and complete analysis of the original model with increased capacity and the split two production line model, several capacity variants were developed that achieve the desired output. These capacities can be seen in Table 4 and Table 5for the single line and dual line respectively. These values can now be used by management to determine the optimal cost process that will allow them increase their capacity. It is the opinion of the authors that the single, dual product production process should be maintained. To achieve the 50% increase in output desired by the system a two line system far exceeds the need. Secondly, in the dual line approach not only is a second production line required but also a complete capacity decrease to the existing line. On the other hand with the single line only a capacity increase is required to achieve the desired system throughput increase.

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