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Design of Manufacturing Cells Pharmaceutical Factory

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ABSTRACT

Cellular manufacturing is an important tool for manufacturing firms which leads to better productivity, focused and specialized manufacturing process. To utilize this important tool, the machines have to be grouped into cells. This work is related to using cellular manufacturing in a pharmaceutical factory with alternative routing. This adds more choices in the decision making process and presses for a better tool to make optimal selection. Several objectives may be considered to improve the productivity objectives such as the total number of exits and planning and scheduling robustness related objectives like bottleneck utilization and load balance between and within the alternative routes. Analytical hierarchical process (AHP) is used as a multi-objective decision making process to evaluate the best scenario amongst generated using simulation as a tool for modeling and evaluating the output for each scenario. Three customer case studies were considered with different preferences and the AHP evaluated the best scenario to fit these preferences. The best scenario can vary from one customer preferences to another but for the current system it turned out to be the same choice.

1. Introduction

A job shop is a multi-stage production system. Each job needs to undergo several operations to become a finished product. In a job shop, only a single machine is capable of processing each operation. This one-to-one relationship will cause blocking of production when any machine breaks down. To reduce the risk of blocking, a flexible job shop forms a group of capable machines for each operation. The term ‘‘flexible’’ comes from the flexibility of routing jobs. If each machine is capable of processing all operations, the shop is very flexible, otherwise, it is partially flexible. Once the machine shop is properly capacitated with the proper number of machines, then two main trends have proven effective in improving the performance of the job shop or flexible job shop: Scheduling and cellular manufacturing. Scheduling is always one of the keys to the success of a production system. Properly utilizing the resources increases machine utilization, reduces work-in-process (WIP) level, shortens time to market, and meets customers’ demands [30]. However, scheduling is a continuous challenge but it must be preceded with equipment arrangement through cellular manufacturing. Cellular manufacturing is used

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to overcome the deficiencies of job shop manufacturing, including excessive setup times and high level of in-process inventories. In cellular manufacturing, part-families are identified and machine cells are formed such that one or more part-families can be fully processed within a single machine cell [27]. Cellular manufacturing systems have shown encouraging results in batch manufacturing environments. Significant improvements can be achieved by grouping machines into cells dedicated to processing a sub-set of the total production. The advantages of cellular manufacturing include reduction in setup times, reduction of material handling times, reduced WIP, increased machine and tool utilization and improved operator utilization [20], throughput time reduction, smaller work in process inventories, manufacturing flexibility increase, product quality improvement and production planning and control simplification [26].

The benefits of cellular manufacturing organization can be strongly affected by the environment uncertainty, such as that associated with resource dependability and demand variability [21, 22]. Flexibility is usually considered in the design and operation of a cellular manufacturing system (CMS) to reduce the risks associated with uncertainty [23, 24]. Among the several types of flexibility, routing flexibility, the ability to use alternative routes inside a cell, or the ability to route parts to cells offering the same processes can strongly affect CMS performance [25]. In environments characterized by low resource dependability, the benefits of routing flexibility can balance the costs of material handling, fixtures, increased set-up times, etc. Therefore, a trade-off between productivity and flexibility can then be searched.

Generally, a cellular manufacturing system is usually designed based on a single machine-part matrix. When the product mix changes, the structure of the machine-part matrix representing the manufacturing system changes too [28]. The performance of the system should be carefully evaluated to address the important objectives relevant to the manufacturing process to avoid creating bottleneck machines, which would deteriorate the schedule quality; on the other hand, one should aim at minimizing costs. Assessing the tradeoff between these possibly conflicting objectives is difficult; actually, it is a multi-objective problem with respect to the load balancing and cost objectives [30]. Many approaches proposed to date base their cell formation on similarity coefficients among the parts. These coefficients can be generated using a coding system [1]. Other methods used to generate similarity measures include the Jaccards similarity coefficient method, a weighted similarity measure [2], process based similarity coefficients [3] and similarity coefficients based on part loading [4]. A different approach towards cellular design is part clustering using the production flow analysis (PFA) which uses a matrix representing the relations among the parts and the machines. The matrix, which is usually binary, is termed component incidence matrix. Many matrix-based methods have been proposed for the cell formation design. Examples are the Rank-Order method [5], the extended Rank-Order method [6], MODROC [7], and a progressive restructuring method [8]. Another approach for clustering is the hierarchical clustering approach, which uses methods such as single linkage clustering [2, 9, 10] and average linkage [11]. Part grouping methods also include optimization techniques such as linear programming [12], integer programming [13], and dynamic programming [4]. A multi-objective cluster analysis was proposed in [14]. Newer methods for clustering use Fuzzy Sets [15], and Neural Network [16]. A good set of introductory references to distributed problem solving can be found in [17-19]. Alternative routing and replicate machine is considered as a flexibility factor that adds to the robustness against uncertainty and has been addressed [32, 33] along with the intercell movement objective [31, 31] or by adding a flexibility objective [31, 32, 34, 35], costs of intercell movements between machine operations and machine investment[31, 37].

Moreover, the Analytic Hierarchy Process (AHP) is a decision analysis technique used to evaluate complex multi-attributed alternatives with conflicting objectives among one or more actors. The process involves hierarchical decomposition of the overall evaluation problem into sub problems that can be easily comprehended and evaluated. The benefits of the AHP include its ability to handle multiple stakeholders with multiple objectives, the inclusion of possible interaction effects and the relative ease of computation. In addition, with the AHP there is no need to explicitly estimate a utility function since the AHP deals with stated preferences at each step [42]. Several alternatives has been used such as Pareto weighting technique or utility weighting for the evaluation of the multi-objective problem. However, these techniques-although are successful in transforming the multi-objective into a single objective might not capture the total relevant experience of the expert or might include subjective mistakes. AHP includes multiple pairwise comparisons of the objectives and the alternatives against the objectives with consistency check, which enables more accurate capturing of the experience and produces a more accurate weighting of the factors. Furthermore, for the cases of complex, manufacturing processes, simulation had been used to model and evaluate the single objective problem or the multi-objective cellular design problem [31, 38, 39, 40, 41]. Simulation is not a cellular manufacturing algorithm, but is a scenario evaluation one. When compared to a scheduler, mathematical model, queuing, Petri net or any other stochastic technique, simulation proves to be the most flexible and accurate modeling technique.

In this work, we have tackled a real case study of cellular manufacturing design in a pharmaceutical factory with all its added complexity of machine set-up time and failure, employee shifts and the alternative routing. This type of complexity makes discrete event simulation the most logical choice for system modeling. We have also addressed the problem as a multi-objective with load balance and productivity in mind and selective a more consistent group of objective functions to reflect load imbalance. Number of scenarios has been generated and AHP was used to evaluate the performance for each alternative.

2. AHP Basic Analysis

Different quality characteristics have diverse responses to the same change in input parameters. Consequently, optimal point for all objectives cannot be achieved concurrently. Manufacturers must then prioritize their objectives. AHP includes a pairwise comparison between each quality measurements to give a specific weight for each objective quality characteristic. In relation to TED, pairwise comparison is done between all experiments for each individual objective characteristic. This in turn gives a weight for the level of achieving of the quality characteristic by each experiment. A simple multiplication between the weight of the quality characteristic and the weight of the experiment and a simple sum will give an overall weight for each process setting. The AHP then includes a hierarchy composed of two main levels, objectives experiments comparison level. The AHP is a systematic analysis technique developed for multi-criteria decision. Its operating mode lays on the decomposing and structuring of a complex issue into several levels, rigorous definition of manager priorities, and computation of weights associated to the alternatives. The output of AHP is a ranking indicating the overall preference for each decision alternative [12]. The development of the AHP model is achieved in three steps [13]: Multi-quality optimization, hierarchical modeling, and evaluation.

The purpose of the AHP is to evaluate the overall achievement weight or score for each process setting (experiment). This is achieved firstly through pairwise comparison between each two quality characteristics and filling the comparison matrix A ($n \times n$) of the second level of the hierarchy, where n is the number of quality characteristics or objectives. Subsequently, the relative weight for each quality characteristic is calculated and a consistency index is calculated as given by the following equations [14]:

$$\mathbf{B} = \mathbf{A} * \mathbf{A} \quad (1)$$

$$\mathbf{C}_j = \sum_{i=1}^{n} \mathbf{B}_{ji} \quad (2)$$

$$Wq = \frac{C}{\sum C_i}. \quad (3)$$

Where, Wq_i is the weight of importance for objective quality characteristic i. Column sum vector is:

$$E_j = \sum_{i=1}^{n} \mathbf{A}_{ij} \quad (4)$$

The Maximum Eigen value:

$$\lambda_{\max} = \mathbf{E} * Wq \quad (5)$$

Consistency Index:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (6)$$

The main advantage of AHP lies with consistency check. Where the comparison is checked using the CI index. Saaty [14] stated that for comparison to be consistent CI<0.10. The above described pairwise comparison is repeatedly performed for all experiments for their performance with respect to each quality characteristic. In this case, We_{ij} is evaluated as the weight coefficient of the experiment j in relation to quality characteristic i. The overall weight for each experimental setting is merely the sum of the multiplication of the weight of experiment j in relation to experiment i and the coefficient of quality characteristic i (See Eq. (7)).

$$w_j = \sum_{i=1}^{n} We_{ij} Wq_i. \quad (7)$$

Where, wj is AHP overall weight achieved by the j^{th} experimental setting.

3. Methodology

This work is related to applying AHP and simulation to cell design in manufacturing for the case of high flexibility and alternative routing. The basic steps for the suggested methodology are:

i. Objectives selection: The objectives should balance between the flexibility and productivity measures.
ii. Pairwise analysis for the objectives to determine the relative weight for each objective.
iii. Scenario generation: Where the possible scenarios are generated based on acceptable changes for the system.
iv. Objectives evaluation for alternative cell design scenarios using simulation.
v. Pairwise comparison for the alternative cell design scenarios against each objective function to evaluate the relative weight.
vi. Evaluating the final performance measure for each scenario.

3.1 Objective Suggestion

Huge emphasis in scheduling and optimization is placed on productivity measures. However, the optimal solution might not be robust enough to face changes in the process, such as machine failure. Therefore, alternative objective function should be considered such as operation cost and/or total exist to consider cases when the bottleneck machine may fail, since the probability of failure increases appreciably with high utilization. A further complication arises if we consider a truly multi-objective approach since assessing the tradeoff between schedule quality and costs is not easy [29]. The traditional scheduling problem lists schedule based objectives such as average flow time, global earliness, lateness, production rate etc. However, these objectives may not be the proper ones to select for balancing the load on different machines. Alternative objectives has been used for cell design such as work in process, intercell movement, total investment. Even these cellular manufacturing objectives may not fit to all case. For example, the work in process inventory (WIP) objective may not fit applications where the pull system is applied. That is a case where the WIP is controlled through a strict pull system. In addition, the investment costs is not applicable to the case when the factory is only rearranging and no new cost are incurred. If each product passes through the same routing as the other, then the intercell movement is a reflection of the number of products produced (total exits in simulation terminology) and is not an independent objective.

Therefore, for successful application of the AHP and the optimization process, the objectives must be selected intelligently. For the problem on hand, the most important objective is the number of products produced in a certain period of time (total number of exits in Promodel terms). This objective is tied to the economics and feasibility of any decision to be made. However, this objective is not conclusive since it does not reflect the balance of the schedule, which is tied to the robustness of the planning and the scheduling process. For this purpose another set of objectives have been included which are related to the machine utilization and delay process. These important objectives reflect machine utilization and planning process robustness. Since already, the load is highly balanced and the process is uniform. We also selected WIP and the average minutes in system. As a summary, in this research, a set of objective functions have been selected which combine between the workstation balance and work in process inventory, these objectives are summarized as below:

i. Objective A: load imbalance 1: load imbalance within cell reflected by the difference in utilization between the maximum utilization difference and the minimum utilization difference.
ii. Objective B: Total exit.
iii. Objective C: load imbalance 2: Load imbalance between cells reflected by the difference in utilization between the bottlenecks of each cell.
iv. Objective D: Work In Process (WIP).
v. Objective E: Average minute in the system.

The following paragraphs demonstrate how the load imbalance between and within cells will be calculated. For example, assume three cells mixing, drying, and milling where the utilization has been calculated using Promodel software as shown in Table 1.

Table 1. Load imbalance 1 calculations.

Cell/ mlc	Mixing%	Drying%	Milling%	Max – Second utilization
Cell 1	30.26	25.79	34.57	4.31%
Cell 2	61.31	24.65	34.57	26.74%
Cell 3	65.94	62.34	23.40	3.6%
Cell 4	54.78	24.65	23.40	30.13%
Cell 5	49.44	19.12	23.91	25.53%
Load balance1= Max- Min				26.53%

The difference between the bottleneck machine utilization and the second in line represents a window of opportunity for improvement. We can improve cell production by switching machines until little difference between the two is noticed. Thus, this imbalance difference reflects the arrangement quality of the machines. The difference between the Max difference and the minimum difference reflects this arrangement quality. The first load imbalance is given by Eq. (8). For each cell and is shown in Table 1 column 5. The objective measure is the difference of the imbalance between the maximum and the minimum imbalance. Ideally, this objective is zero that is there no difference within the cell between the different machines. However, it can be zero if all the cells have the same imbalance that is the max imbalance - min imbalance are equal which means that all arrangement are equal.

Load imbalance = within cell (max. utilization – Second utilization). (8)

For the current production line the total imbalance equals = 30.13 – 3.6 = 26.53.

Table 2 shows the same values of utilization as that of Table 1, however the values are arranged to give load imbalance 2. The maximum utilization is correlated to the production rate for each cell and Ideal cells are arranged evenly.

Balance load2 (for each cell) = Max Util. cell- Min Util. cell. (9)

Table 2. Load balance 2 calculations.

Cell/ mlc	Mixing%	Drying%	Milling%	Max
Cell 1	30.26	25.79	34.57	34.57
Cell 2	61.31	24.65	34.57	61.31
Cell 3	65.94	62.34	23.40	65.94
Cell 4	54.78	24.65	23.40	54.78
Cell 5	49.44	19.12	23.91	49.44
Load balance2= Max- Min				31.37%

4. Case Study

An XYZ local pharmaceutical company is interested in transforming its powdering process department from the current parallel machine configuration into cellular manufacturing. The company has three main processes: granulation, milling, blending as demonstrated on Fig 1. Granulation process consists of mixing the active ingredients and drying it, in this process the required batch (lot size) divided into many mixtures (premixes) according to machine capacity. Afterward, the Milling machine consists of crashing the mixtures after granulation to a small grain size. Finally, Blending process, which combines the mixtures (premixes) after milling according to the required batch size, so the final blend, is now ready to proceed to the next process (tableting).

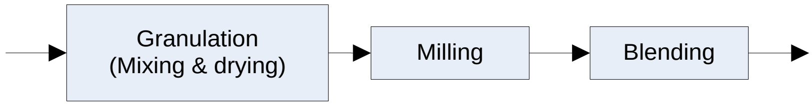

Fig 1. Basic processing steps in the powdering department.

Furthermore, in the XYZ pharmaceutical company each machine consists of different types as shown in Table 2, where variability exists due to difference from the manufacturer source. The name given to each machine is the same name known by the workers and recorded in the factory records.

Table 3. List of the machines in the XYZ company.

Mixing machine	Drying machine	Milling machine
Mixer E	Aeromatic C	Fitz mill
Mixer L-150 A	Aeromatic A	Oscillator
Mixer L-150 B	Oven	Glatt cone mill
Mixer H	Glatt dryer	
Glatt mixer		

In a usual manufacturing process, machine is not available 100% of the time. It is customary to have set-up time and machine failures. This add's up to the complexity of the cellular manufacturing processes and if these are significant, then simple models might not be suffice. The powder machine's is subjected to the following setup and failure types:

i. Dry cleaning: A type of cleaning that is made to the machine after each premix of the same product.
ii. Wet cleaning: A type of cleaning that is made to the machine when the concentration of the same product changes.
iii. Full cleaning: A type of cleaning that is made between different products.
iv. Repair: An operation that fixes the machine when a malfunction occurs.
v. Preventive maintenance: Periodic maintenance (every 3 months) to check the machine state.

5. Data Collection and Distribution Fitting

In this research paper, data has been collected for the process time, setup time and failure time over one year based upon the company logbooks, the setup and failure time have been classified into the five types as discussed above. Subsequently, the data for each machine and each type has been fitted to the best distribution as shown in Table 4.

6. Building the Simulation Model

This section and subsection illustrate the building of the basic model representing the current situation in the factory. This model serves as the base against which other alternatives are evaluated, the current situation in the factory includes the following manufacturing cells, and the percentage of the products manufactured on each cell is demonstrated on Table 5. The company will allocate specific products to each line for reducing cleaning and setup times. Thus, specific percentages of production is associated with each cell, which reflects the products that are allocated to that cell.

Cell 1: Mixer E, Aeromatic C, and Fitzmill.
Cell 2: Mixer 150A Aeromatic A Fitzmill.
Cell 3: Mixer 150 B Oven Oscillator.
Cell 4: Mixer H, Aeromatic A Oscillator.
Cell 5: Glatt mixer Glatt dryer Glatt cone mill.

Table 4. A sample of the distribution fitted for the cleaning process and the repair.

Machine	Full cleaning		Wet cleaning		Repair	
	time	Frequency	time	Frequency	Time	Frequency
Mixer E	N(7.69, 3.55) HR	After processing 15 product	4.87 HR	42 day		
Aeromatic C	B(1.14, 1.47, .5, 12.8) HR	After processing 15 product	N(3.86, 1.73) HR	L(2.43, .988) day	E(3.95) HR	L(1.5, 1.25) day
Fitz mill	B(2.74, 4.19, 2, 17.4) HR	After processing 17 product	ER(1.11, 2) HR	E(9.34) day	6.5 HR	22 day
Mixer L-150 A	T(3.05, 12, 17) HR	After processing 17 product	N(4.19, 1.73) HR	N(17.6, 12.4) day	2 HR	120 day
Aeromatic A	N(8.57, 3.94) HR	After processing 17 product	N(4.05, 1.98) HR	E(7.5) day	ER(3.45, 1) HR	E(.1,12.4) day
Mixer L-150 B	ER(2.46, 3) HR	After processing 18 product	E(5.03) HR	E(8.54) day	3.13 HR	33.5 day

Table 5. The percentage of products manufactured on each cell.

Cycle	Total # of premix	Percentage (%)
1	607	25.92 %
2	545	23.27 %
3	312	13.32 %
4	545	23.27 %
5	333	14.22 %
Sum	2342	100%

Table 5 shows the different product percentages allocated to each cell. The arrivals process reflects the orders inter-arrival time fitted. Following to arrival, the orders are distributed to the cells according to product type percentages as shown in Fig 2.

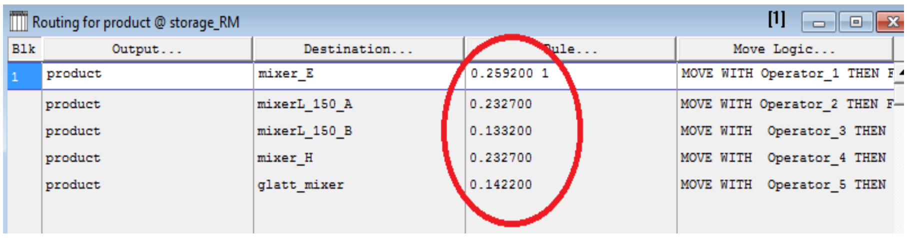

Fig 2. Routing window.

On the developed Promodel simulation software, the products have been developed as entities and material handling as path networks. Furthermore, machines, operators, and maintenance operators were represented as locations, resources, and downtimes. The working schedule were represented using the shifts in Promodel. The arrival was used to enter the products in and the processing was used to control the product flow in the model. Fig 3 shows a layout of the powdering department.

6.1. Validation

After developing the simulation model for the current process, the model has been validated using both expert's point of view and model outcome. On the first validation techniques a set of experts has been selected to validate the process visually, those experts include production manager, maintenance manager, and general manager in addition to the main researcher. In the second technique, the outcome from the simulation model has been compared to the real live process outcome over a ten months period. Within this period, the actual outcome is 2342 orders while the simulation model provides 2335 orders so we get around 0.3% error. Thus, the model may be considered as valid and accurate.

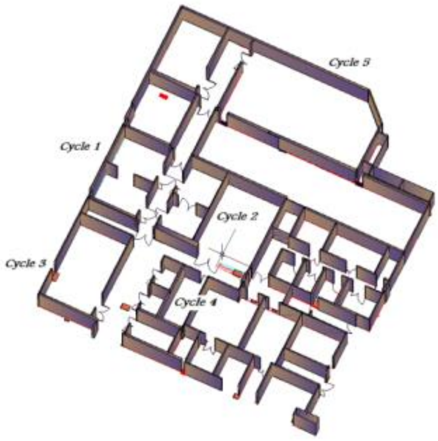

Fig 3. Layout of powdering department.

ENTITY ACTIVITY

Entity Name	Total Exits	Current Quantity In System	Average Minutes In System	Average Minutes In Move Logic	Average Minutes Wait For Res, etc.	Average Minutes In Operation	Average Minutes Blocked
product	2335	1320	48659.60	295.75	466.04	613.42	47284.37

Fig 4. Entity activity output.

7. The Scenarios

Process experience is the major factor in scenario generation, the bases of scenario generation is to have variants of the same process that are feasible and applicable. After a set of brainstorming session with the management team, nine scenarios are suggested based upon changes in product percentage devoted to each cell as shown in Table 6 and machine arrangement variation as shown in Table 7.

Table 6. Changing in percentage of cell Input.

Scenario #	Mixer E	mixer L-150A	mixer l 150 B	mixer H	glatt mixer
1	0.2	0.2	0.2	0.2	**0.2**
2	0.2327	0.2	0.2	0.2	**0.2592**
3	0.3	0.175	0.175	0.175	**0.175**
4	0.175	0.175	0.3	0.175	**0.175**
5	0.167	0.167	0.25	0.166	**0.25**

Table 7. Machine rearrangement based on feasibility.

Scenario	Arrangment
6	- Cell1: Mixer E → Oven→ scillator.. - Cell2: Mixer L-150 A → Aeromatic C→ Fitz mill. - Cell3: Mixer L-150 B→ Aeromatic A→ Fitz mill. - Cell4: Mixer H →Aeromatic A→Oscillator. - Cell5: Glatt Mixer →Glatt dryer →Glatt Cone Mill.
7	- Cell1: Mixer E →Aeromatic A→ Fitz mill. - Cell2: Mixer L-150 A→Aeromatic C→Fitz mill. - Cell3: Mixer L-150 B→Oven→Oscillator. - Cell4: Mixer H→Aeromatic A→Oscillator. - Cell5: Glatt Mixer→Glatt dryer→Glatt Cone Mill.
8	- Cell1: Mixer E→Aeromatic C→Fitz mill. - Cell2: Mixer L-150 A→Aeromatic A→Fitz mill. - Cell3: Mixer H→Oven→Oscillator. - Cell4: Mixer L-150 B→Aeromatic A→Oscillator. - Cell5: Glatt Mixer→Glatt dryer→Glatt Cone Mill.
9	- Cell1: Mixer E→Aeromatic A→Fitz mill. - Cell2: Mixer L-150 A→Aeromatic A→Fitz mill. - Cell3: Mixer L-150 B→Oven→Oscillator. - Cell4: Mixer H→Aeromatic C→Oscillator. - Cell5: Glatt Mixer→Glatt dryer →Glatt Cone Mill.

8. Results Analysis and Discussion

8.1 Results

For each scenario, the five objective functions have been obtained using the Promodel software outcome as shown in Table 8. It is obvious that different scenarios provide totally different results and this stresses the need for a suitable selection scheme. The worst and best for each objective is highlighted and there is no clear optimal solution.

Table 8. Objective summary for each scenario.

	Objective A	Objective B	Objective C	Objective D	Objective E
Scenario 1	26.53%	2886	31.37%	23.50	2914.88
Scenario 2	33.985%	2725	20.74%	23.60	2987.49
Scenario 3	26.47%	3079	24.36%	23.34	3023.90
Scenario 4	21.01%	2593	31.7%	24.04	2851.94
Scenario 5	27.74%	2729	35.94%	24.44	3055.80
Scenario 6	39.62%	2630	34.6%	24.80	2975.87
Scenario 7	35.88%	2770	29.6%	23.65	3103.88
Scenario 8	17.31%	3334	26.29%	22.98	2940.28
Scenario 9	33.02%	2605	26.39%	24.41	3051.41

8.2 AHP Analysis

8.2.1 Sample Objective Scoring

Objective A (load balance 1) is selected to show the AP calculations. We can notice that the range of values: maximum value = 39.62% and minimum value = 17.31%. Load imbalance should be kept to minimum value. The score can be calculated by mapping the two scales as shown in Fig 5 using Eq. (9).

The score =

(maximum value –scenario value) / (Maximum value -Minimum value)*Scale length +1 (9)

=(39.62 - 26.53%)/(39.62 – 17.31) * 8+1= 5.7.

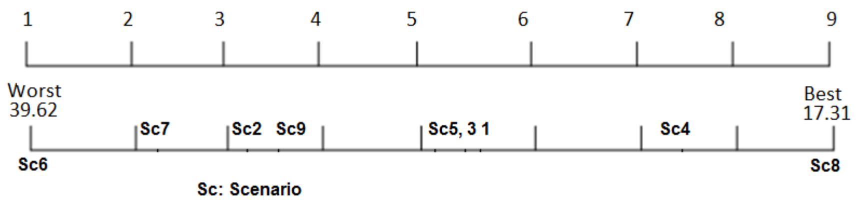

Fig 5. Schematic analysis to illustrate objective mutual comparison generation matrices.

The summarized score for each scenario versus the objective function has been calculated in Table 9. These values can be compared to the results in Fig 5 for validation. Furthermore, the score for each objective function at each scenario has been calculated as shown in Table 10.

Table 9. Objective and score summary.

	Objective A	Score
Scenario 1	26.53%	5.7
Scenario 2	33.985%	3.0
Scenario 3	26.47%	5.7
Scenario 4	21.01%	7.7
Scenario 5	27.74%	5.3
Scenario 6	39.62%	1.0
Scenario 7	35.88%	2.3
Scenario 8	17.31%	9.0
Scenario 9	33.02%	3.4

Table 10. Scenario performance scoring for the different objectives.

	Objective A	Objective B	Objective C	Objective D	Objective E
Scenario 1	5.7	4.2	3.4	6.7	7.0
Scenario 2	3.0	2.4	9.0	6.3	4.7
Scenario 3	5.7	6.2	7.1	7.4	3.5
Scenario 4	7.7	1.0	3.2	4.3	9.0
Scenario 5	5.3	2.5	1.0	2.6	2.5
Scenario 6	1.0	1.4	1.7	1.0	5.1
Scenario 7	2.3	2.9	4.3	6.1	1.0
Scenario 8	9.0	9.0	6.1	9.0	6.2
Scenario 9	3.4	1.1	6.0	2.7	2.7

8.2.2 Mutual Comparison Matrix for the Scenarios

Table 11 shows the Objective A, mutual comparison matrix "A". Each item in the matrix is generated using the scores in Table 10. For example, the item in cell 1x2 shaded is equal to scenario 2 score/scenario 1 score =5.7/3.0=1.88. It represents how well scenario 2 is performing when compared to scenario 1. This Table represents the "A" matrix and the sum of the columns is the E vector according to Eq. (4). (See Section 2).

Table 11. Objective a mutual comparison.

	1	2	3	4	5	6	7	8	9
1	1	1.88	1	0.74	1.08	5.69	2.43	1.69	1.69
2	0.53	1	0.53	0.39	0.57	3.02	1.29	0.9	0.9
3	1	1.89	1	0.74	1.09	5.72	2.44	1.7	1.7
4	1.35	2.54	1.34	1	1.46	7.67	3.28	2.28	2.28
5	0.92	1.74	0.92	0.69	1	5.26	2.25	1.56	1.56
6	0.18	0.33	0.17	0.13	0.19	1	0.43	0.3	0.3
7	0.41	0.78	0.41	0.31	0.45	2.34	1	0.7	0.7
8	1.58	2.98	1.57	1.17	1.71	9	3.84	2.67	2.67
9	0.59	1.11	0.59	0.44	0.64	3.37	1.44	1	1
Sum (E)	7.56	14.26	7.54	5.61	8.19	43.07	18.4	12.79	12.79

As discussed on the AHP Section (Section 2), at this stage the B matrix will be calculated, then column C is calculated by taking the sum value for each row after that these values are normalized to calculate the weight of importance for objective quality characteristic (Wq) as shown in Table 13.

Table 12. B matrix and C and Wq vectors for objective a mutual pairwise comparison.

B Matrix									C	Wq
8.93	16.62	8.93	6.32	9.63	50.72	21.34	5.63	15.19	143.31	0.132
4.7	8.75	4.7	3.33	5.07	26.71	11.24	2.97	8	75.47	0.069
8.93	16.62	8.93	6.32	9.63	50.72	21.34	5.63	15.19	143.31	0.132
12.18	22.67	12.18	8.63	13.13	69.18	29.11	7.69	20.72	195.49	0.179
8.32	15.48	8.32	5.89	8.97	47.25	19.88	5.25	14.15	133.51	0.122
1.56	2.9	1.56	1.1	1.68	8.85	3.72	0.98	2.65	25	0.023
3.71	6.91	3.71	2.63	4	21.07	8.87	2.34	6.31	59.55	0.055
14.33	26.68	14.33	10.15	15.46	81.41	34.26	9.04	24.38	230.04	0.211
5.29	9.84	5.29	3.74	5.7	30.02	12.63	3.33	8.99	84.83	0.078

Afterward, the Maximum Eigen value (λ_{max}) has been calculated using Eq. (5) and the consistency index (C.I**)** is calculated using Eq. (6) as clarified below:

λ_{max} **=** (0.132*7.6) + (0.069*14.3) + (0.132*7.5) + (0.179*5.6) + (0.122*8.2) + (0.023*43.1) + (0.055*18.4) + (0.211*4.8) + (0.078*12.8) = 9.0000.
C.I = (9.0000-9) / (9-1) = 0.000.
R.I (for n=9) = 1.45.
C.R = 0.00000/ 1.45
= 0.00000 < 0.1 (accepted).

The normalized weight for each objective function at each scenario has been calculated and summarized in Table 13; these values are proved to be consistent.

Table 13. Summary of the normalized weights for the scenarios.

	Objective A	Objective B	Objective C	Objective D	Objective E
1	0.132	0.135	0.081	0.132	0.132
2	0.069	0.079	0.215	0.070	0.070
3	0.132	0.203	0.169	0.133	0.133
4	0.179	0.033	0.077	0.178	0.178
5	0.122	0.080	0.024	0.122	0.122
6	0.023	0.046	0.041	0.023	0.023
7	0.055	0.095	0.104	0.054	0.054
8	0.211	0.293	0.145	0.209	0.209
9	0.078	0.037	0.144	0.078	0.078

8.2.3 Best Scenario Evaluation

Case 1: The planner is more concerned with the total number of products produced and time in system. Different cases will be discussed on the following subsections. In this case, the planner is concerned more on the total number of products produced and the total time on the system. The mutual comparison of the objectives are calculated in Table 14, afterward the B and C matrix are calculated in addition to the weight of importance for objective quality characteristic (Wq) as shown in Table 15.

Table 14. Objectives rating for the case 1 scenario.

	Objective A	Objective B	Objective C	Objective D	Objective E
Objective A	1.0	0.1	1.0	0.2	0.1
Objective B	9.0	1.0	9.0	1.8	1.0
Objective C	1.0	0.1	1.0	0.2	0.1
Objective D	5.0	0.6	5.0	1.0	0.6
Objective E	9.0	1.0	9.0	1.8	1.0
Sum E	25.0	2.8	25.0	5.0	2.8

Table 15. B matrix, C, and We vectors for planner interest case 1.

B Matrix					C	We
1.37	2.48	12.4	1.37	12.4	30.02	0.0398
12.4	22.44	112.2	12.4	112.2	271.64	0.3598
1.37	2.48	12.4	1.37	12.4	30.02	0.0398
6.92	12.52	62.6	6.92	62.6	151.56	0.2008
12.4	22.44	112.2	12.4	112.2	271.64	0.3598

Afterward, the Maximum Eigen value (λ_{max}) has been calculated using Eq. (5) and the consistency index (C.I**)** is calculated using Eq. (6) as clarified below:

λ_{max} = 25.0 (0.040) + 2.8 (0.360) + 25.0 (0.040) + 5(0.200) + 2.8 (0.360) = 4.999=5.
C.I =(n- λ_{max})/ n-1= (5-5)/(5-1) = 0.
when n=5 R.I.= 1.12 , C.R=C.I/R.I=0/1.12=0 < .1 (acceptable).

At this stage, the AHP overall weight achieved by the experimental setting (w_j) is calculated for the first scenario, the summarized overall weight for each scenario is summarized in Table 16. These results clarify that scenario eight is the optimal followed by three then one for the above case.

weight of first scenario= (.1277)(.17)+(.0968)(.4)+(.0851)(.13)+(.14)(.2)+(.1739)(.1) = .116882.

Table 16. Scenarios overall rating for planner preference case 1.

Scenarios	Weight
1	0.13112
2	0.07904
3	0.15964
4	0.12176
5	0.10296
6	0.03200
7	0.07076
8	0.23668
9	0.06588

Case 2: Planner more concerned with the load balance. If the load balance is of utmost importance, then the same steps calculated in the previous case study will be performed at this stage, the summarized overall weight for each scenario is summarized in Table 17 which show that scenario eight is the best followed by three and two respectively.

Table 17. Scenarios overall ratings for planner preference case 2.

Scenarios	Weight
1	0.110762
2	0.132571
3	0.151762
4	0.12781
5	0.07800
6	0.03181
7	0.077381
8	0.185571
9	0.104333

Case 3: Customer concerned with time in system then WIP and time in system. If the work in process and time in system is of utmost importance, then the same steps calculated in the previous case study will be performed at this stage. The summarized overall weight for each scenario is summarized in Table 18 which show that scenario eight is the best followed by four and three respectively.

Table 18. Scenarios overall ratings.

Scenarios	Weight
1	0.129294
2	0.079059
3	0.139235
4	0.163529
5	0.113765
6	0.025412
7	0.059353
8	0.210176
9	0.079471

9. Conclusions

This work is applied to cell design for alternative routing in a pharmaceutical factory based on a multi-objective analytical hierarchical process technique. Several ways can be used to generate feasible scenarios, experience and process knowledge was used in this work. The objectives used to evaluate were load within cell, Total exit, load imbalance between cells, Work In Process (WIP) and Average minute in the system. The optimal of each objective was in a different scenario. So, the optimal cannot be readily evaluated. We have transformed the optimal evaluation into a score of 1 to 9, and the optimal for each customer preference was obtained. The scenario arrangement according to each customer preferences was different, but the optimal was the same as Scenario 8.

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