RESEARCH PAPER

Design and Analysis of a Robustly Optimized Kanban System for a single stage production

Laxmikant Joshi [1], Atul Aradhye [2], Nitin Morkane [3] , Mahesh Joshi [4]

[1*]Assistant Professor, SKN Sinhgad College of Engineering, Pandharpur.
[2] Assistant Professor, SKN Sinhgad College of Engineering, Pandharpur.
[3] Assistant Professor, SVERI's College of Engineering, Pandharpur.
[4]Assistant Professor, SKN Sinhgad College of Engineering, Pandharpur.

Abstract
This paper intends to propose a simulation-based robustly optimized approach for scheduling of a single-stage kanban system for single stage production unit. The design of experiment (DOE) method is used to frame the robust schedule for the scheduling of the raw material arrival.. The main objective is to reduce the raw material and workin process inventory. The variables affecting inventory are classified into two categories, namely, the controllable and the uncontrollable. With Full factorial method, these two types of variables are crossed mutually to get the estimated and variance values of total schedule deviation. Further, this paper also focuses on how to optimize the scheduling of raw material arrival for a single stage production unit.

Key Words: Design of Experiment; DOE; Kanban; Optimization; Robust; Simulation

How to cite this article: Joshi L, Aradhye A, Morkane N, Joshi M. Design and Analysis of a Robustly Optimized Kanban System for a Single Stage Production. Int J Drug Deliv Technol. 2026;16(20s): 799-812. DOI: 10.25258/ijddt.16.20s.80

Introduction

This case study intends to reduce the inventory in the industry. Philosophies of lean management lead to reduce inventories. Large volumes of stocks stored near the production unit not only hide the problem of making the entire shop idle but also it may generate interferences with the work of the operators with decreased safety. In this situation, the introduction of decentralized storage areas located between the production line and the central warehouse gives the possibility to have frequent deliveries of small batches of components (Emde 2012). In the automobile sector, the decrease of a batch size of components with an increase in variation has led to a diffusion of mixed-model assembly lines Kaustav Kundu, Matteo Rossini, Alberto Portioli-Staudacher, 2019). Feeding of stripps for the punching operation forms the inventory, which depends on variables like demand, material availability, processing time and availability of machines. Further, the computational cost of such inventory would increase dramatically if these random variables are combined. This makes a robust solution hard and challenging for the single stage production scheduling, as there are multi-dimensional random variables.

Furthermore, this case study seeks to reduce the computational cost of the robust numerical simulation to the greatest extent when designing a schedule of a kanban system for the single stage production system. The proposed methodology is built upon the philosophy of design of experiment (D.O.E.) to determine the most impactful decision variables.

The industry under study has many divisions like pressure vessel, acoustic unit, job fabrication, fastners and washers. For our study, we have considered only washer manufacturing section. The washer manufacturing unit was around one kilometer away from the main branch. The company has its own transportation facility. The raw material in the form of sheets with different thickness and finished products in the form of washers of different specifications are stored in the main branch. The production planning and control unit is operated from main branch only.

In our case study, we have studied the washer manufacturing unit. We have concentrated on the inventory of this unit only. Currently, Production Plannning and Control department defines the schedule on monthly basis. Accordingly, the required raw material is issued to the concern manufacturing unit. The company has its own vhehicle for transportation to shift material. Production Plannning and Control department always takes care of transportation cost while shifting of materials from main branch to concern manufacturing unit.

The most significant disadvantage of this system is that material varification at the manufacturing unit is not done frequently. The raw material inventory at the manufacturing unit is found to be increasing day by day. The manufacturing unit is following last in first serve system. The old sheets of raw material were found in bad condition. While inspection, few bad sheets were found rejected, resulting in loss of material. In this case study, it is shown how to reduce the raw material inventory by introducing kanban system for a single stage production system.

Review of Literature

Shubham Singh (2021) have proposed to apply robust optimization to deal with uncertain data. Yue Zhao et al. (2022) explained how to protect the system from the disturbances caused by uncertainties. In literature,

Author for Correspondence:

robust optimization for uncertainties has been seen to be categorized into two types, namely, the analytic and the simulation-optimization. The analytic robust optimization is formulated with constraints in the mathematical model to reflect its robustness. Shubham Singh et al (2021) introduced the primary linear programming robust optimization model, which used the maximal values of uncertain coefficients as inputs to ensure robustness. Alexandre Cesar Balbino Barbosa Filho et al. (2022) significantly improved the performance of the linear programming robust optimization model by adding few parameters to control the degree of conservatism for every constraint. Most of the uncertain problems are not tractable easily with analytic robust optimization. Many researchers have proposed robust optimization using the technique of simulation-optimization (Parnianifard A et al., 2022). The simulation-based robust optimization can be formulated with the spirit of DOE to analyze the output data by experiments. The simulation-based robust optimization is also called as robust design. It has deeper roots than analytic robust optimization with mathematical models in the engineering field (Hans-Georg Beyer 2007). The robust design primarily aims at determining controllable parameters with which the best performance could be found despite uncertainty (Chaolin Song et al. 2024). A comprehensive review of this method could be found in Gjerloev (2025). The main goal of robust design is to formulate a frame against the threat of system performance degradation. It should also preserve an excellent system performance under a set of unworthy scenarios. The effectiveness of robustness is evaluated by a penalty function on the bad-scenario set. The bad-scenario set is identified for the current solution by a threshold, which is restricted on a reasonable-value interval.

Kanban is one of the best tools to control inventory for robust optimization in the setting of batch formulation. Although the design of kanban was created for the manufacturing system, it has also been used to solve the feeding problem for an assembly line (Kaustav Kundu, 2019) and also for the supermarket to minimize inventory including stock-out of items (Maurizio Faccio et al., 2013). Although a number of servers are an essential component required to reduce handling costs, the optimal number of kanbans will reduce inventory without considering handling costs (Lei Yang et al., 2009). Moretti et al. (2022) developed a typical procedure that computes the number of servers to formulate batches and kanban analytically. Through simulation, they found the optimized delivery frequency. Felix T. S. Chan (2001) stated that the batch size of the job in the process also has a major impact on the efficiency of the kanban system Kaustav Kundu, 2019) have modelled a kanban system by using the queuing theory. They have used simulation to obtain the optimal number of servers along with a minimum batch size to avoid stock-out with reduced cost. Yu Q et al. (2023) claimed that the main task of robust kanban scheduling is to handle the uncertainties.

Methodology

In the present system, all the raw material in the form of sheets have been issued to the production unit as per the requirement from the plant. The sheets were stored in the yard at specific locations. As per demand, the sheets were cut to form strips of predefined size. For cutting operation, mostly last come first serve system was followed. The strips were supplied to machines for punching operation. Few machines were paddle operated and few machines were automats. The processing time varies accordingly. In one stroke, one washer is produced. The main objective of this study is to provide a robust kanban system to reduce inventory. Figure 1 shows the flowchart of methodology for our study.

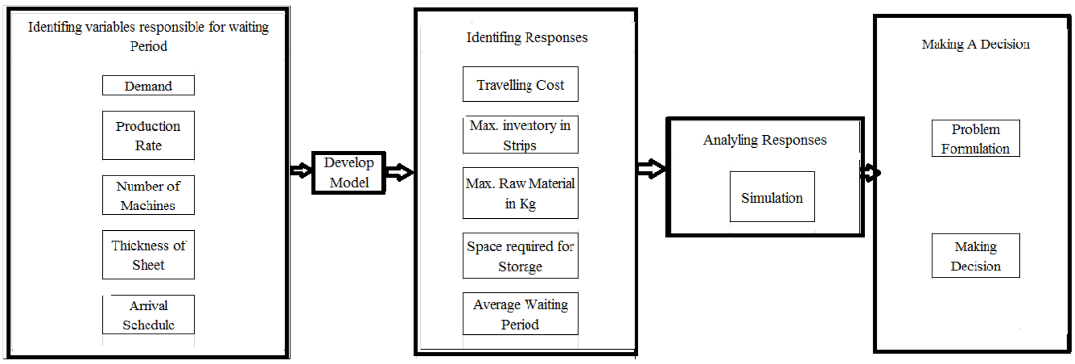

Fig 1. Flow chart of methodology

Step 1 Identifying Variables Responsible for raw material inventory

The inventory is mainly classified as raw material, work in process and finished goods inventory. In this case, we will concentrate mostly on raw material inventory. The raw material inventory mostly depends on the arrival rate and processing rate. If the processing rate is more than arrival rate, there is no possibility of raw material in queue waiting for operation. But if the arrival rate is more than processing rate, there will be continuously increase in raw material inventory. If the processing rate is fixed but arrival rate is unpredictable or undefined, it is tedious to calculate raw material inventory. In such cases, it is very important to develop a model. To develop a model, it is necessary to study all the variables responsible for inventory. The variables can be segregated into two categories controllable and uncontrollable. While developing the robust optimal schedule, we will design the schedule of controllable variables with concern with all uncontrollable variables. In this case study, the aim is to set the controllable input variable to reduce raw material inventory. Accordingly, a model has to be developed so that we could detail the process to determine the robust schedule for the kanban system. The crucial thing to formulate the D.O.E. is to identify the controllable and uncontrollable variables that have significant impact on the raw material inventory. The previous work, such as Daganzo (2009), Xuan et al. (2011), and Yan et al. (2012), all determined the uncertain supply of raw material as the primary cause of raw material inventory.

For this sake, the controllable and uncontrollable variables are:

Uncontrollable variables:

- Demand (A)
- Production Rate (B)

Controllable Variables:

- Number of Machines (C)
- Thickness of Sheet (D)
- Arrival schedule (E)

The experimental area of parameters

Firstly we should assume that all the controllable and uncontrollable factors are continuous so that we could choose out design in the analogous intervals (i.e., the experimental area of the parameter, E.A.P.) as follows:

E.A.P. for controllable variables.

- C Є [1, 2, 3, 4, 5, 6, 7,…]
- D Є [0.8, 1.0, 1.6, 2.5,….]
- E Є [A1, A2, A3,……A13]

Where Є denotes the possible lower and upper bound of the scheduled number of machines for manufacturing of washers. At the present situation, the industry is having two manual operated and one automat. Thickness of sheet is depends on the specifications of washer, and subdivided into 0.8 to 2.5 mm thickness. The schedule of raw material's arrival is sub divided into 5 numbers. It depends on the capacity of transportation vehicle, daily requirement and safety stock. The arrival pattern is decided according to monthly , fortnightly, weekly, twice a week and daily respectively.

E.A.P. for uncontrollable variables.

The demand for each category of washers is in kg. For our understanding, we have converted it into number of washers. The demand for each type of washer varies from month to month. Production Planning and Control department has subdivided the demand in monthly basis for each type of washer. Mostly this demand for each category of washers is uncontrollable. In the same way, the production rate is also different for different machines. It also varies with the operator skill. In this case study, we have focused on M4 to M12 type of washers. The demand varies for each category of washers. The levels of demand and production was created and listed below.

- A Є[12,00,000, 12,50,000, 13,00,000]   (washers/month)
- B Є[45,000, 50,000, 55,000]   (washers/ shift)

Step 2 Developing a Model

The proposed model is of single stage production system. This model should include feeding mechanism of raw material to machines for processing. A framework should be created to decide the feeding mechanism of jobs with controlled inventory stock (Battini et al. 2009). The feeding mechanism may not be effective for all components (Caputo and Pelagagge, 2011). Battini et al. (2010) have done similar work, where the choice is extended at each component's level, and the comparison of different feeding policies for different components has been relatively well discussed. Faccio (2014) worked on product mix and investigated the break even points of different feeding strategies.

Developing a model requires defining the real situation of the system. The input data should be neatly specified, and output should be clearly defined. A mathematical model had been developed by Limere et al. (2012) to support the analysis and the selection of the better one.

In this case study, we formulated multiple simulation models based on real projects currently in operation (Thomas R. Robbins, 2007). These models were designed so that the behavior of the system should be observed under various realistic operating conditions. Each model has unique characteristics. It was noticed that the demand of washers is one of the significant variables having a significant effect on the raw material inventory as well as finished goods inventory. The demand of each category of washers is unpredictable. Here data of demand for each washers is collected and compared with each other with mathematical tools (Thomas R. Robbins, 2007).

Finally, the data is separated according to specifications of washer. The washers having same thickness are grouped in one category. Separate models are developed for all these types of categories. While designing a model, two sections have been proposed with two different transitions. The first one deals with all the movement of the raw material (sheets) from main branch to manufacturing unit. The second one controls the work in process inventory, which includes cutting of sheet into stripps and processing these stripps on machines to produce washers. As per the F.C.F.S. basis, arrived sheets will cut into stripps of predefined size and formation of kanabn. These kanban will be provided to machine to produce washers.

Assumptions

For any model to be considered valid, few assumptions must be made.

1. Kanban is considered empty according to the bottom of container rule. It means that the kanban card is made available for each Kanban containg predefined number of stripps. (Vatalaro& Taylor, 2005).
2. Each kanabn will be separated from other one, each kanban can be resupplied independently from the store. A similar kind of assumption is made in Emde and Boysen (2012).
3. Congestion (in terms of the traffic of operators) is not an issue for transportation from main branch to manufactruring unit, and this is clear with most of the articles in literature since they do not mention this issue.
4. The manager issues next container only when present container is empty. (Hobbs, 2003).
5. There are no express kanbans, like in other kanban systems. It means all the kanbans will follow the first in first serve rule. However, it is logical to assume that, in a situation of complete stock-out, in the present kanban, stripps in the next kanban needed to issue for machine are the most urgent since without it the downstream stages would be idle anyway.
6. The processing time on machine follows the exponential distribution. This proposed assumption is backed by a similar one done by Karmarkar and Kekre.
7. The collection/distribution of kanban cards in the line can be only virtual. This assumption is desirable for modeling purposes. It is shown later, though; it does not affect the optimality of the solution.
8. One kanban strictly corresponds to one container . This assumption is the most public in the literature (Liubimov O et al., 2023).
9. In most of the literature, there is provision for the scrapped products. It has been sent to a different location, where they are reworked and ultimately converted to a finished product, and this is a recognized practice in the manufacturing industry. In our case, while deburring process, all the defective units were considered as scrap, and ther is no chance for rework in this case, so no different location for rework.

Modelling Kanban System

The model for washer manufacturing machine is just like a single stage production system. In this process, the arrived sheets are cut into stripes of predefined size. Then this bunch of strips, are treated as kanban, and loaded to a particular mahine for processing. As we increase the number of machines, production rate will increase resulting in reduction in raw material inventory. So in this model, we can also increase the number of machines to reduce the raw material inventory.

A simplified model of the production process with the kanban system is shown in figure 2. This simplified model is only to aid in the explanation of the kanban system being built in this model.

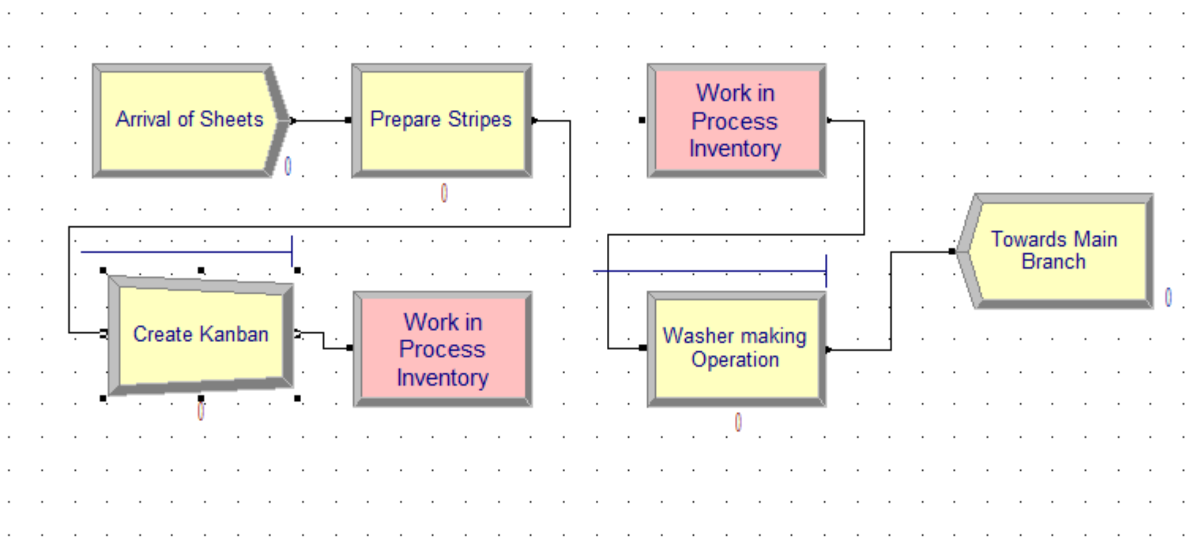

Figure 2 Modelling Kanban System

This model is prepared in ARENA Software, where the arrival of sheets is considered as scheduled arrival. It is connected to the necessary process of the batch. Here we are creating batches of a predefined stripes in the cutting section. When the sheets arrives in the manufacturing unit, it is cut into strips of predefined size. The number of stripes in a single trolley (kanban in our case) is also predefined. All the arrived sheets are cut into stripes as per the schedule provided. As the signal arrives from the production unit, next trolley is issued to the specified machine and the empty trolley received from the production unit is provided to cutting machine for refilling.

Step 3 Analyzing the inventory with simulation

Design of Experiment (D.O.E.) is a mathematical method to organize the sequence of experiments to obtain the ultimate experimental result. It is a very important tool to achieve systematic results after performing small-scale tests. After designing the experimental objectives, one has to select the sampling method. Further, choosing the input factor with levels of all variables, the expected output is to be determined. In the last, perform the experiments to observe the response. This response will be helpful for the decision-maker to take a decision. (Ramachandran and Tsokos, 2015)

The D.O.E. method has been widely used to obtain the robust parameter or combination of parameters. It considers the functions of both controllable and uncontrollable variables. Simulations or experiments are carried out to find out the relationship between the inputted combination of controllable and uncontrollable variables and the corresponding output. During the process, two orthogonal arrays have been designed for controllable factors. Uncertain factors are also used to arrange the experiments (Chen et al., 2015; Esen and Turgut, 2015). Orthogonal array specified for controllable factors is denoted as the inner O.A. In the same way, Orthogonal array designed for uncontrollable factors is referred to as the outer O.A. Process ensures that the factor combinations presented in the two O.A.s are orthogonal to each other to avoid sampling any two combinations of factors with interdependent levels. Three representative objective functions (also called loss functions) are widely used to examine the robust performance of the system (Ranjit, 2004):

a. Larger the better,

b. Smaller the better, and

c. On-target, minimum-variation.

Sometimes, three objective functions are unproductive for the robust parameter design. The computation cost of the objective function via simulation is relatively high. As a result, in some advanced methodologies, cross experiment design was used, rather than its objective functions as well as statistical process (Dellino, 2009; Dellino et al.,2010; Dellino et al., 2014). But, full factorial is one of the best methods for determining the optimal combination of controllable parameters to produce a product or process. It optimizes the parameter combination to the uncertainty based on definite statistical principles. The full factorial array is used to find the best controllable variables based on a statistical analysis of experimental or simulation results. The traditional method, to deal with such deviation problem, is to eliminate the super lousy part. It can also be done by having strict control over the material and the process to decrease the deviation through product detection. These methods are not economical, also are found to be challenging to accomplish the technical objective. In our case, the full factorial array could save computational time to decide the number of machines and arrival pattern to minimize inventory.

Step 4 Making a Decision

In D.O.E. analysis, the output gives the decision maker a complete idea of all the probable outcomes. D.O.E. collects all the simulated output for all the input factors with all possible levels. The results generated may be helpful for the decision-maker to choose the best course of action. Moreover, the results from the quantitative tools can be used just as a guideline for a decision-maker to make a robust decision. It can not be used as a replacement for personal judgment in the case of human resources scheduling. If all the input information is correct, it can be guaranteed the best decision (Amiya Kumar Pattanayak et al., 2019).

The solution with our method

The detailed steps are performed as follows:

Step 1. Set the levels of the controllable variables:

Number of Machines : [1, 2, 3, 4, 5, 6]; Thichkness of sheet in mm : [0.8. 1.00. 1.6, 2.0, 2.5], and Arrival Schedule [A1, A2, A3, A4, A5,…A13].

Step 2. Set the levels of uncontrollable variables.

Demand washers per month : [12,00,000, 12,50,000, 13,00,000], and Production Rate washers per shift : [45000, 50,000, 55,000].

Step 3. Generate the inner O.A. for orthogonally combining the controllable variables by full factorial Array. In this case, we have three controllable variables, which have two, five, and five levels, respectively. Consequently, inner O.A. should be designed. At the same time, generate the outer O.A. for the uncontrollable variable production rate and arrival schedule.

Table Number 1

Controlable Parameters with Their Values		
Controlable Parameters with Their Values	Level	Values
Washer Specifications and Combinations	15	M4, M6, M8, M12, M14, M4&M6, M4&M8, M4&M12, M4&M14, M6&M8, M6&M12, M6&M14, M8&M12, M8&M14, M12&M14
Arrival Paters	5	A1, A2, A3, A4, A5

Table Number 2 Experimentation Details

Expt. No.	Washer Specification	Arrival Schedule	Expt. No.	Washer Specification	Arrival Schedule	Expt. No.	Washer Specification	Arrival Schedule
1	M4	A1	26	M4 & M6	A1	51	M6 & M12	A1
2	M4	A2	27	M4 & M6	A2	52	M6 & M12	A2
3	M4	A3	28	M4 & M6	A3	53	M6 & M12	A3
4	M4	A4	29	M4 & M6	A4	54	M6 & M12	A4

5	M4	A5	30	M4 & M6	A5	55	M6 & M12	A5
6	M6	A1	31	M4 & M8	A1	56	M6 & M14	A1
7	M6	A2	32	M4 & M8	A2	57	M6 & M14	A2
8	M6	A3	33	M4 & M8	A3	58	M6 & M14	A3
9	M6	A4	34	M4 & M8	A4	59	M6 & M14	A4
10	M6	A5	35	M4 & M8	A5	60	M6 & M14	A5
11	M8	A1	36	M4 & M12	A1	61	M8 & M12	A1
12	M8	A2	37	M4 & M12	A2	62	M8 & M12	A2
13	M8	A3	38	M4 & M12	A3	63	M8 & M12	A3
14	M8	A4	39	M4 & M12	A4	64	M8 & M12	A4
15	M8	A5	40	M4 & M12	A5	65	M8 & M12	A5
16	M12	A1	41	M4 & M14	A1	66	M8 & M14	A1
17	M12	A2	42	M4 & M14	A2	67	M8 & M14	A2
18	M12	A3	43	M4 & M14	A3	68	M8 & M14	A3
19	M12	A4	44	M4 & M14	A4	69	M8 & M14	A4
20	M12	A5	45	M4 & M14	A5	70	M8 & M14	A5
21	M14	A1	46	M6 & M8	A1	71	M12 & M14	A1
22	M14	A2	47	M6 & M8	A2	72	M12 & M14	A2
23	M14	A3	48	M6 & M8	A3	73	M12 & M14	A3
24	M14	A4	49	M6 & M8	A4	74	M12 & M14	A4
25	M14	A5	50	M6 & M8	A5	75	M12 & M14	A5

For experimentation, full factorial design matrix is selected and shown in table number 1. Total 75 experimentations have been decided with 5 replications.

Step 4. Simulate to calculate the value of the travelling cost, maximum inventory in terms of strips and weight, space required to store the raw material in the form of bins and the waiting period of raw material.

Optimization of Arrival Schedule through MCDM Tool

Now let us try to optimize the schedule through Multi-Criteria Decision Making tool. The waiting period, travelling cost, inventory and number of bins required is known through Arena and Matlab software. For optimization, only important input controllable parameters should be considered. The parameters are shown in the following table Number 1.

The full factorial design matrix for experimentation is shown in Table 2. According to full factorial design, total 30 experiments have been decided as per the selected design criteria with five replications. Thus, finally 30 experiments have been conducted for all the proposed design. Thus total 150 experments have been performed for the proposed study.

Here, as per table Number 2, all the experiments were simulated in Arena and matlab software for five times and the response values were recorded.

The same is graphically represented in following figures. Figure 3 represents the effect of Arrival patern on the transportation Cost. It is observed that as the arrival pattern is changed from A1 to A5, the transportation cost increases.

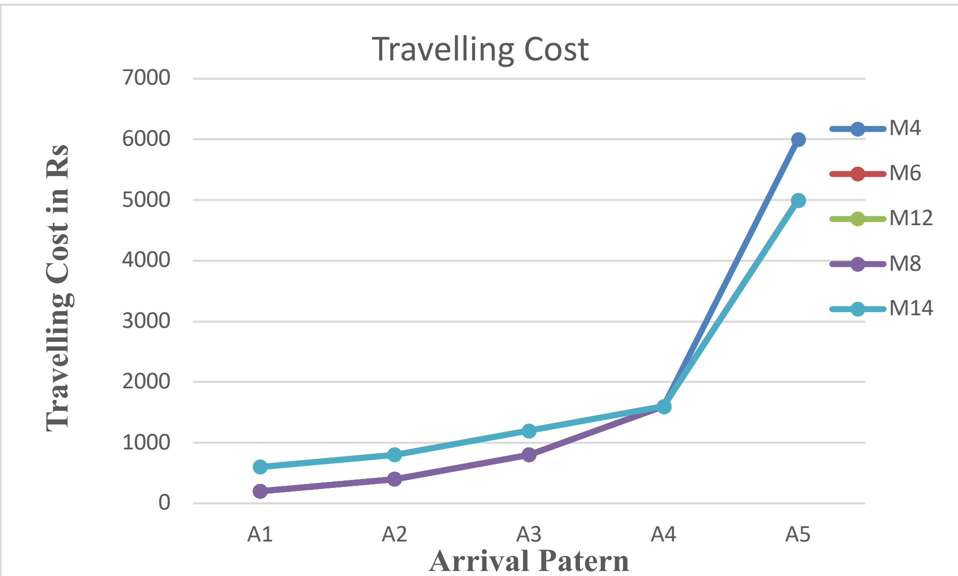

Figure 3 Effect of Arrival patterns on Travelling Cost

Figure 4 represents the effect of Arrival patern on the raw material inventory, in the form of strips. It is observed that as the arrival pattern is changed from A1 to A5, the raw material inventoruy decreases.
Figure 5 represents the effect of Arrival patern on the space required for raw material inventory, in the form of bins. It is observed that as the arrival pattern is changed from A1 to A5, the space required for raw material decreases.

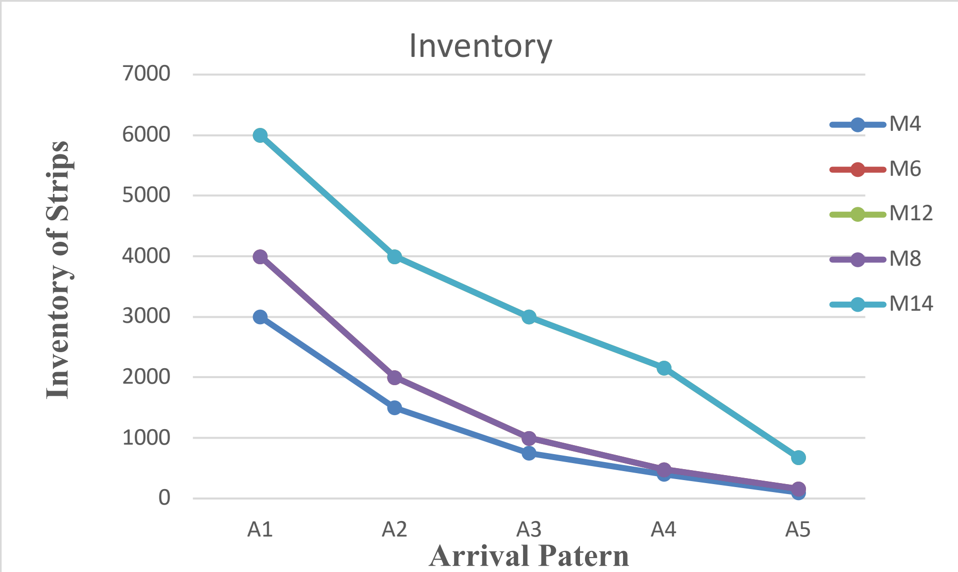

Figure 4 Effect of Arrival patterns on Raw material Inventory in form of Strips

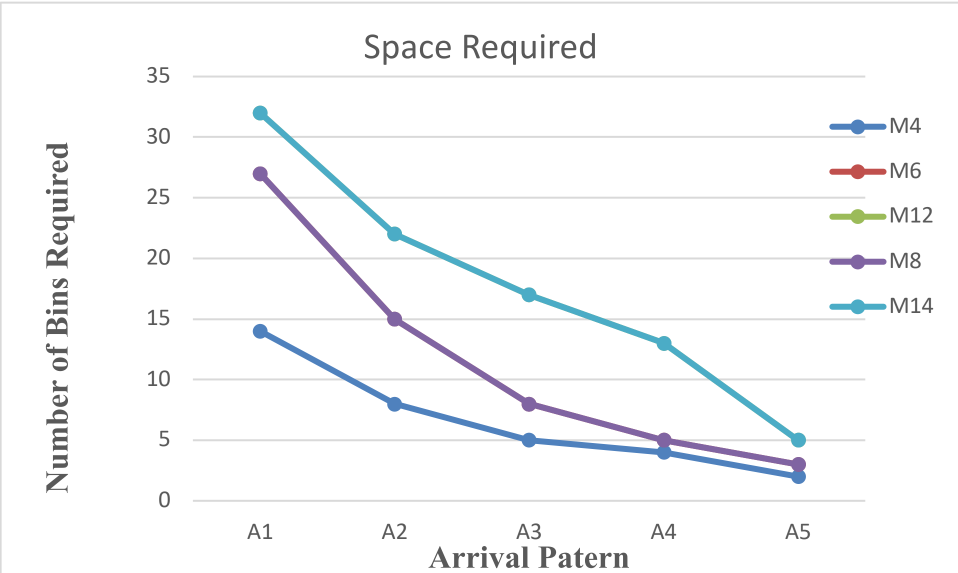

Figure 5 Effect of Arrival patterns on space required

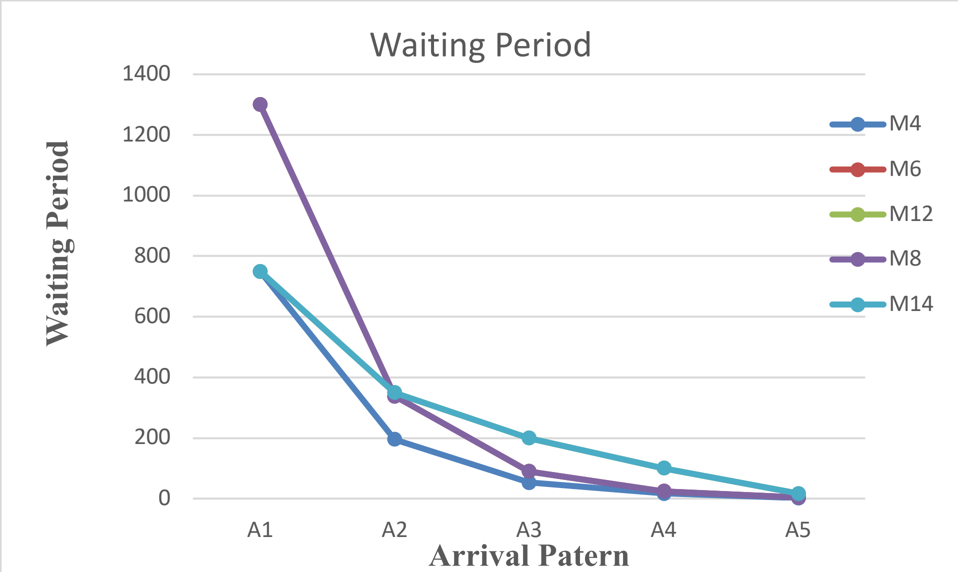

Figure 6 Effect of Arrival patterns on waiting Period

Figure 6 represents the effect of Arrival patern on the waiting period of raw material in the yard. In another way, one may treat it as holding cost, but as we are dealing with only manufacturing unit, we will consider it as waiting period.. It is observed that as the arrival pattern is changed from A1 to A5, the waiting period decreases.

As shown in figure 4, 5,and 6 as we move from A1 to A5 the Transportation cost increases, but the value of inventory, bins required decereses . The waiting period is also decreases as we move from A1 to A5. Overall Evaluation Criteria is used to find the optimal solution.

As the out put parameters, transportation Cost, Inventory, Number of bins required and waiting period are to be considered, the weight percentage of OEC are formulated accordingly as below.

Table Number 3 Weight percentage of different OEC criteria

Out put Criteria	OEC1	OEC2	OEC3	OEC4
Transportation Cost	0.25	0.33	0.33	0.25
Inventory	0.25	0	0.33	0
Number of bins required	0.25	0.33	0	0.25
Waiting period	0.25	0.34	0.34	0.5

Table Number 4 OEC Values for all Experiments

Washer Specification	Arrival Schedule	OEC1	OEC2	OEC3	OEC4
M4	A1	0.250	0.330	0.330	0.250
	A2	0.681	0.736	0.742	0.737
	A3	0.839	0.859	0.869	0.878
	A4	0.867	0.860	0.879	0.888
	A5	0.750	0.670	0.670	0.250
M6	A1	0.250	0.330	0.330	0.330
	A2	0.736	0.734	0.814	0.731
	A3	0.883	0.867	0.893	0.866
	A4	0.899	0.871	0.914	0.870
	A5	0.750	0.670	0.670	0.670
M12	A1	0.250	0.330	0.330	0.330
	A2	0.604	0.623	0.681	0.621
	A3	0.730	0.723	0.788	0.722
	A4	0.812	0.789	0.849	0.787
	A5	0.750	0.670	0.670	0.670
M4&M6	A1	0.25	0.33	0.33	0.33
	A2	0.678	0.737	0.734	0.655
	A3	0.840	0.867	0.855	0.808

	A4	0.867	0.868	0.857	0.830
	A5	0.739	0.670	0.656	0.656
M4&M12	A1	0.250	0.330	0.330	0.330
	A2	0.736	0.734	0.814	0.731
	A3	0.886	0.869	0.917	0.868
	A4	0.899	0.871	0.893	0.870
	A5	0.750	0.670	0.670	0.670
M6&M12	A1	0.250	0.330	0.330	0.330
	A2	0.737	0.734	0.815	0.732
	A3	0.885	0.868	0.916	0.867
	A4	0.898	0.871	0.893	0.870
	A5	0.750	0.670	0.670	0.670

Four weightage criteria were decided and accordingly OEC values for a the experiments are tabulated in table number 3. In OEC analysis, according to higher is the best criteria, the maximum values are highlighted in the table number 4. From this study, it is clear that, the optimal solution is A4 for all the washers and combinations of washers. Figure 6 represents a graphically analysis of OEC values for all arrival Paterns as a case study for M4 washers.

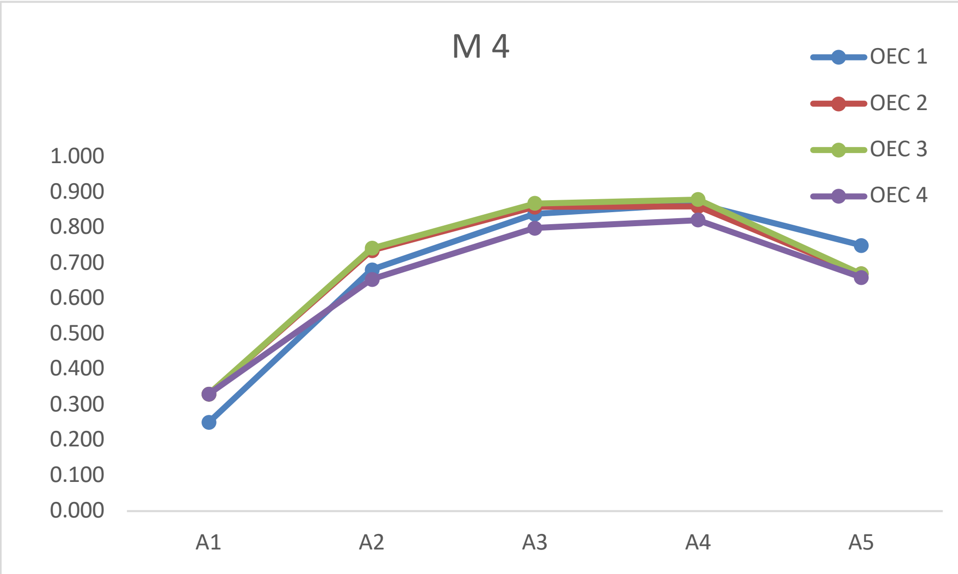

Figure 6 OEC Values for Arrival Patterns

TOPSIS Analysis

TOPSIS method consists to calculate a coefficient of closeness for each alternative based on distances between the focused alternative and the positive and the negative best solutions. The optimal alternative has the shortest distance from the positive-best solution (PBS) and the extreme from the negative best solution (NBS). Suppose a multi criteria decision making process has p alternatives A1, A2, A3….Ap and q criteria C1, C2, C3…. Cq . Each alternative is evaluated with respect to the q criteria. All the values/ratings are assigned to alternatives with respect to decision matrix denoted by X(Kij)pxq. Assuming W= (w1, w2, w3…..wq) be the weight vector criteria, satisfying $\sum_1^q w_i = 1$ The TOPSIS method can be summarized on the following steps

Now let us take a case of washer of specification M12. The values for responses for all types of arrival schedule are tabulated below. Table Number 5 indicates the values of response parameters for arrival schedules. Table number 6 is a general normalized matrix.

Table Number 5 Values of Response Parameters for Arrival schedules

Sr. No	Arrival Pattern	Travelling Cost	Inventory	Number of Bins Required	Waiting Peroid
1	A1	600	6000	32	750
2	A2	800	4000	22	350
3	A3	1200	3000	17	200
4	A4	1600	2160	13	100

5	A5	5000	680	5	17

Table Number 6 Normalized Matrix

Arrival Pattern	Travelling Cost	Inventory	Number of Bins Required	Waiting Peroid
A1	0.110	0.492	0.717	0.875
A2	0.146	0.369	0.493	0.408
A3	0.219	0.266	0.381	0.233
A4	0.292	0.084	0.291	0.117
A5	0.913	0.084	0.112	0.020

Here we will multiply the column of normalized matrix by the associated weights. Then we will get weighted normalized decision matrix as shown in following table number 7.

Table Number 7 Weighted Normalized Decision Matrix

Arrival Pattern	Travelling Cost	Inventory	Number of Bins Required	Waiting Peroid
A1	0.027	0.123	0.179	0.219
A2	0.037	0.092	0.123	0.102
A3	0.055	0.066	0.095	0.058
A4	0.073	0.021	0.073	0.029
A5	0.228	0.021	0.028	0.005

The positive best and a negative best alternatives are determined, respectively, as follows in table number 8.

Table Number 8 Euclidean Distances from Positive Best and Negative Worst Alternatives

Euclidean distance from Positive Best alternative	Euclidean distance from Negative worst alternative
$S_1^+ = 0.20083$	$S_1^- = 0.28102$
$S_2^+ = 0.23331$	$S_2^- = 0.15384$
$S_3^+ = 0.25702$	$S_3^- = 0.10093$
$S_4^+ = 0.28591$	$S_4^- = 0.06840$
$S_5^+ = 0.28102$	$S_5^- = 0.20083$

Computed the Euclidean distance of each alternative from positive best and negative worst alternatives: the distances for each alternative are, respectively, given by table number 9.

Table Number 9 RC Values and its Rank

RC Number	Value	Rank
RC1	0.417	5
RC2	0.603	3
RC3	0.718	2
RC4	0.807	1
RC5	0.583	4

According to rank of RC, alternative number 4 (i.e. Arrival pattern of twice a week) is the optimal solution. Accordingly the values of RC for all the weight criteria are tabulated below in table number 9

Table Number 10 RC Values for all Weight Criteria

	RC1	RC2	RC3	RC4
A1	0.417	0.4292	0.4528	0.5239
A2	0.603	0.6274	0.6495	0.6287
A3	0.718	0.7360	0.7630	0.7010
A4	0.807	0.7980	0.8382	0.7699
A5	0.583	0.5708	0.5472	0.4761

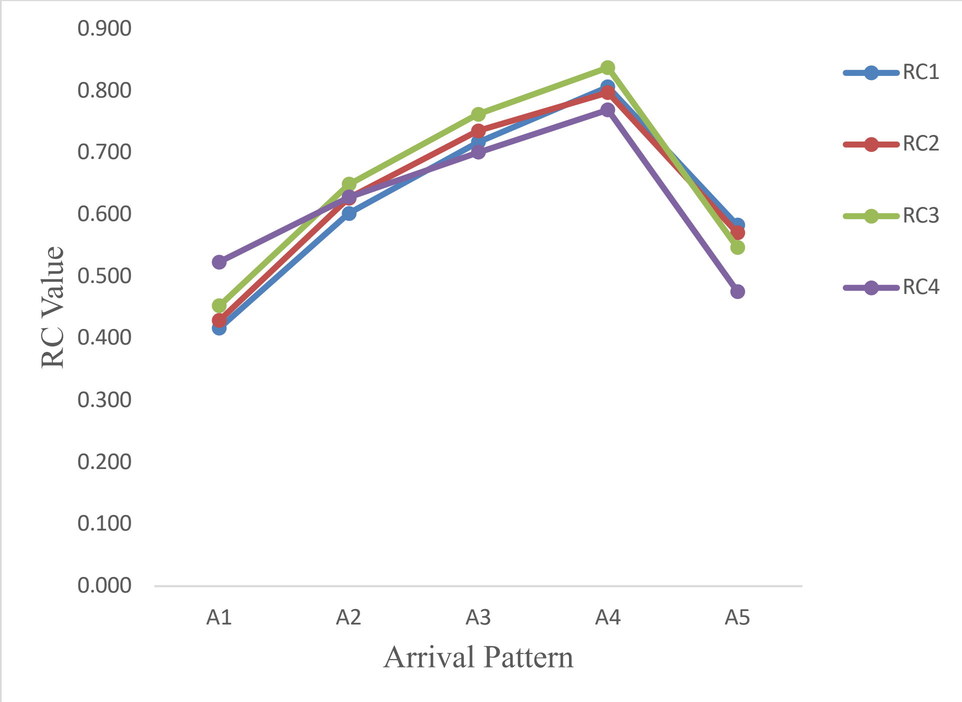

Figure 7 RC values for Arrival Patterns

In this study, to optimize the arrival pattern, we have designed few arrival patterns. A1 indicates monthly requirement. It means monthly requirement stock will be issued to the manufacturing unit at the start of the month. Arrival schedule A2 means the raw material is dispatched to the manufacturing unit twice in a month. In simple words, requirement for fifteen days will be issued in a single lot. Arrival schedule A3 means the monthly requirement is issued to the manufacturing unit four times in a month. In the case of A3 arrival pattern, weekly demand will be issued to the unit in a single lot. A4 indicates the monthly requirement is issued to the manufacturing unit eight times in a month. Here, twice a week, concern requirement should be supplied to the manufacturing week. Arrival schedule A5 means the daily requirement is issued to the manufacturing unit on daily basis.

Conclusion

To find the optimal design, firstly, we findout the different variables having impact on the output. Then we have applied backward elimination theory to eliminate the less effective variables and focused on the variables, having significant impact on the output.

After application of D.O.E., it is found that A4 is the optimal arrival schedule for our case. In case of OEC, the higher value is the best value for the criteria. It is highlighted in the table 4. In all the cases, the arrival schedule of A4 gives higher value, means optimal solution.

If we observe the TOPSIS tool, higher is better, and from the above fig. 10, it is observed that as for all the weightage factors, RC value is maximum for A4. So A4 means arrival pattern of twice a week is the optimal solution.

In the present situation, the industry is using A1 pattern, which means the monthly requirement is issued to the manufacturing unit at the start of month. If there is any change in the production schedule, according to the new schedule, next material is issued to the manufacturing unit. In such cases of changed schedule, after completion of new schedule, the manufacturing unit is asked to continue the previous schedule. In such cases, there is no control on the raw material stock available at manufacturing unit.

Imperial Case Study

Let us take a case study of present system of a combination of M6 and M12 washers. The requirement is of M6 washers in terms of sheets are 88 sheets per month, and that of M12 is 100 sheets per month. At present all 188 sheets are issued to the manufacturing unit at the start of month. In this case, we will concentrate on transportation cost, Maximum Inventory in terms of number of stripps and in Kg also. Most important is waiting period. One may term this as holding cost also, but as in this manufacturing unit, we are not purchasing these sheets, we will term it as waiting period. The following figure indicate the comparison between the present arrival schedule and proposed optimised arrival schedule.

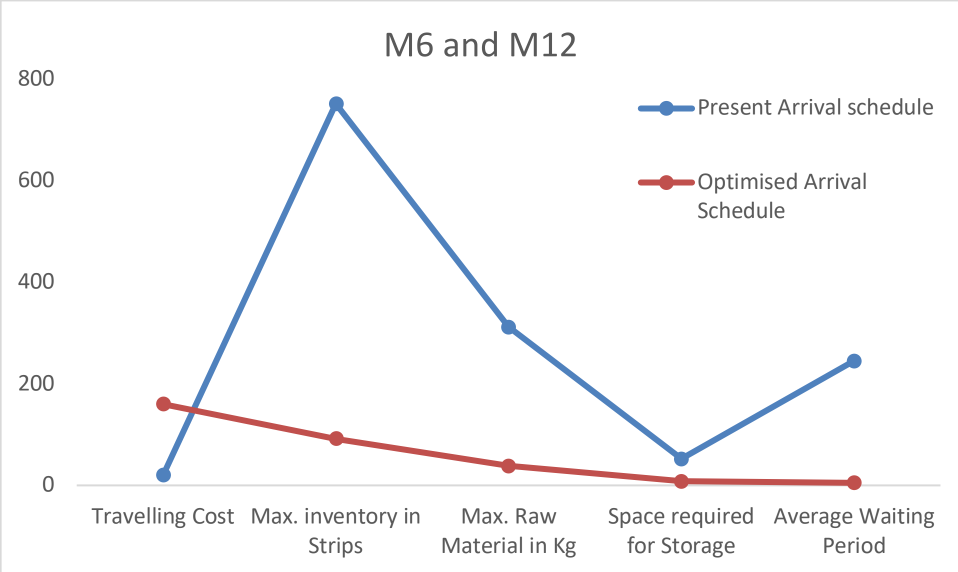

Figure 8 Comparison of output parameters for Optimized Arrival Schedule with present Arrival schedule

From this above figure 7, it is clear that, Travelling Cost is increased by eight times. Maximum inventory is decreased by 8.17 times. Maximum inventory in terms of kilogram is also decreased by 53 times. Most important for any small scale industry is the space required. By adopting the proposed optimal arrival schedule, it is found that the space required to store the strips is reduced by 6.5 times. The average waiting period is reduced by 50 times with the proposed arrival schedule.

Method comparison and the derived decision information

To evaluate the performance of the proposed method, necessary comparisons have been made with other few important scheduling methods while offering a robust schedule for the arrival schedule of a single stage production unit. Daganzo (2009) has proposed a schedule-based control. Xuan (2011) formulated simple optimization control, while Yan (2012) used a method based on robust-optimization. The unique method proposed in this paper can be denoted as a D.O.E. method. The comparison is made according to the Travelling cost, waiting period, space required, maximum inventory for all the proposed 5 scheduling patterns.

Figure. 9 shows the profile of the Travelling cost, waiting period, space required, maximum inventory with arrival pattern of monthly, fortnightly, weekly, daily and Optimized schedule.

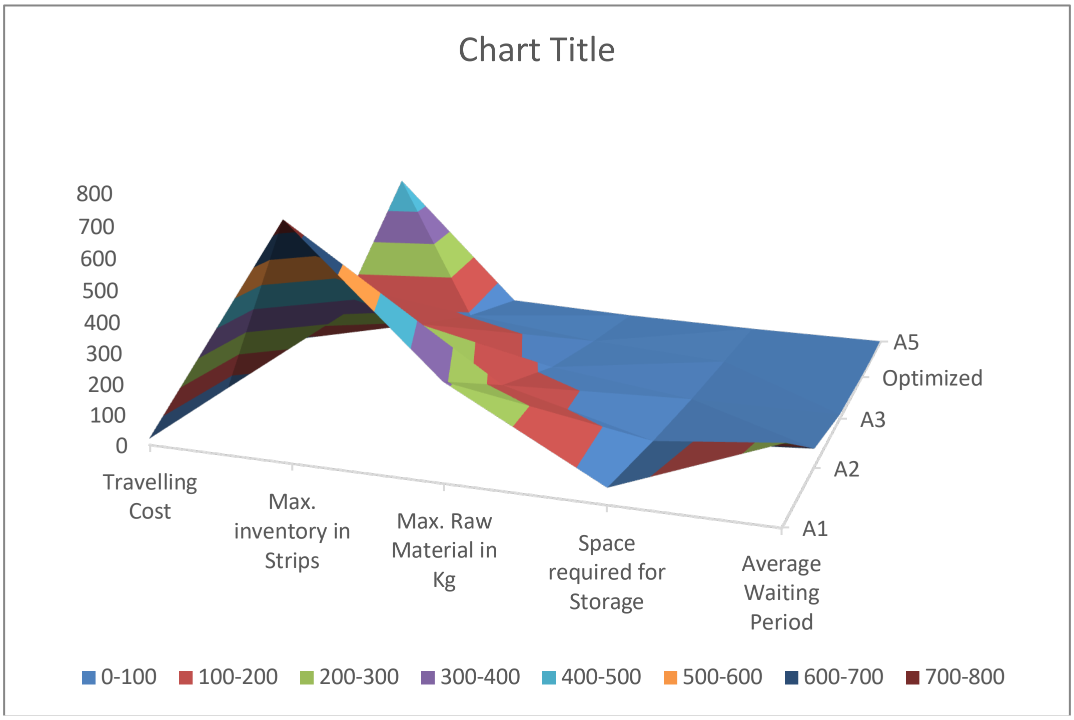

Figure 9 Effect of Optimized Servers on Travelling Cost, Inventory, Space Required and Waiting Period

We compare the outputs of robust design in terms of the Travelling Cost, Inventory, Space required and Waiting Period. If we compare to arrival schedule of A1, means monthly arrival pattern, the transportation cost is increased by 8 times. The maximum inventory in terms of sheets or strips is reduced by 8.17 times. The inventory in terms of kilogram is reduced by 8.21 times. The space required in terms of bins are reduced by 6.5 times. The most important i.e. waiting period is reduced by 49 times. If we compare these parameters with A2 Arrival schedule, thn it is observed that, the transportation cost is increased by 4 times. The maximum inventory in terms of sheets or stripps is reduced by 4.08 times. The inventory in terms of kilogram is reduced by 4.10 times. The space required in terms of bins are reduced by 3.5 times. The most important i.e. waiting period is reduced by 12.6 times. If we compare these parameters with A3 Arrival schedule, then it is observed that, the transportation cost is increased by 2 times. The maximum inventory in terms of sheets or stripps is reduced by 2 times. The inventory in terms of kilogram is reduced by 2 times. The space required in terms of bins are reduced by 1.75 times. The most important i.e. waiting period is reduced by 3.2 times. If we compare these parameters with A5 Arrival schedule, then it is observed that, the transportation cost is reduced by 3.15 times. The maximum inventory in terms of sheets or strips is increased by 2.85 times. The inventory in terms of kilogram is increased by 2.92 times. The space required in terms of bins are increased by 2 times. The most important i.e. waiting period is also increased by 6.25 times.

Discussion and conclusion

This paper recommends a D.O.E. method to project a robust schedule for a single stage production system to reduce raw material inventory. The work includes analysing of arrival pattern from the main branch to manufacturing unit, designing a suitable kanban system and preparing a robust schedule of arrival of raw material from main branch to manufacturing unit. After collection of data, different types of variables, responsible for inventory are categorized into controllable and uncontrollable. In this work, we adopt full factorial model to analyse these variables. Five arrival schedules were proposed to find the optimal solution.

Our finding differs from that of published work, which suggests to follow with a fixed schedule for a long time. Conversely, we recommend to use multiple products option to have a robust schedule. Comparing findings with the relevant studies, we consider that the implications of using D.O.E. for our proposed work could be derived as follows.

Firstly, from the perspective of single stage production schedule design, D.O.E. has never been applied in this research field. Thus this work provides a new attempt to introduce this popular study method in the field of single stage production system. Secondly, for the practical approach of this schedule determination of raw material, it does not require too many large scale calculations. However, the accuracy of robustness is very important for the scheduling of arrival pattern of raw material. Hence, the method proposed in this work, provides an interesting solution for a small scale production unit to determine the practical solution without any complicated computation.

Finally, the method offered in this case study compromises the transportation cost as well as the holding cost or in other terms, waiting period of raw marterial with robustness and accuracy when the relatively small-scale computation is required. At the same time, the proposed model could necessarily save the cost of trial operation for adjusting the patterns of arrival schedules. The optimal controllable factor could bring good robustness to resist external disturbances due to those different kinds of uncertain situations that have been considered with variable cross operations with the full factorial method.

Finally, our research also has many improvement aspects as follows:

(a) Although the proposed method could effortlessly find out the optimal solution of the combination of controllable variables, it may not be used to determine the "exact solution" or the excellent robust solution of the controllable variable. Instead, we follow the ideal combination of parameters, which could bring the best system performance. As well, selecting which combination should be according to the experience of the engineer or the practitioner. This might limit the applicable value of the proposed methodology.

(b) After comparing to the present literature, it is revealed that our proposed method does not apply to the very large-scale problem for the single stage production system. It even may not be used to determine the waiting period in the large scale production in emergency, when the unit is asked to work in two shifts or with overtime of 4 hours, depending upon the urgency of a particular specific washer.

References

1. Emde, S., & Boysen, N., "Optimally routing and scheduling tow trains for jit-supply of mixed model assembly lines," European Journal of Operational Research, 217(2), 287-299, (2012).
2. Kaustav Kundu, Matteo Rossini, Alberto Portioli-Staudacher, “A study of a kanban based assembly line feeding system through integration of simulation and particle swarm optimization,” International Journal of Industrial Engineering Computations 10(3):421-442, (2019)
3. Shubham Singh, M.P. Biswal, “A robust optimization model under uncertain environment: An application in production planning”, Computers & Industrial Engineering, Volume 155, 2021,
4. Yue Zhao, Zhi Chen, Andrew Lim, Zhenzhen Zhang, “Vessel deployment with limited information: Distributionally robust chance

constrained models, Transportation Research" Part B: Methodological, Volume 161, 2022,

5. Shubham Singh, M.P. Biswal, "A robust optimization model under uncertain environment: An application in production planning", Computers & Industrial Engineering, Volume 155, 2021,
6. Alexandre Cesar Balbino Barbosa Filho, Sergio Mauro da Silva Neiro, "Fine-tuned robust optimization: Attaining robustness and targeting ideality" Computers & Industrial Engineering, Volume 165, 2022.
7. Parnianifard A, Mumtaz S, Chaudhary S, Imran MA, Wuttisittikulkij L. "A data driven approach in less expensive robust transmitting coverage and power optimization." Sci Rep. 2022.
8. Hans-Georg Beyer, Bernhard Sendhoff, "Robust optimization – A comprehensive survey", Computer Methods in Applied Mechanics and Engineering, Volume 196, Issues 33–34, 2007
9. Chaolin Song, Abdollah Shafieezadeh, Rucheng Xiao, Bin Sun, Analytical robust design optimization for hybrid design variables: An active-learning methodology based on polynomial chaos Kriging, Reliability Engineering & System Safety, Volume 250, 2024,
10. Gjerloev, A., Grieco, L., Lamé, G., & Crowe, S. Using design of experiments with discrete event simulation in operational research: a review. Journal of Simulation, 1–17, 2025
11. Kaustav Kundu, Matteo Rossini, Alberto Portioli-Staudacher, A study of a kanban based assembly line feeding system through integration of simulation and particle swarm optimization, International Journal of Industrial Engineering Computations, Volume 10, 2019
12. Maurizio Faccio, Mauro Gamberi, Alessandro Persona, Kanban number optimisation in a supermarket warehouse feeding a mixed-model assembly system, International Journal of Production Research, Volume 51, 2013
13. Lei Yang, Xiaopeng Zhang, Mingyue Jiang, An optimal Kanban system in a multi-stage, mixed-model assembly line, Journal of Systems Science and Systems Engineering, Volume 19, 2009
14. Moretti, E., Tappia, E., Mauri, M. et al. A performance model for mobile robot-based part feeding systems to supermarkets. Flex Serv Manuf J 34, 580–613 (2022)
15. Felix T. S. Chan, Effect of kanban size on just-in-time manufacturing systems, Journal of Materials Processing Technology, Volume 116, 2001
16. Yu Q, Zhang Y, Zhao H, Yu T, Li L. A robust optimal scheduling system based on multi-performance driving for complex manufacturing systems. Sci Rep. 2023 Oct 7;13(1):16911
17. Carlos F. Daganzo, A headway-based approach to eliminate bus bunching: Systematic analysis and comparisons, Transportation Research Part B: Methodological, Volume 43, Issue 10, 2009
18. Xuan, Y., "Increasing the flow capacity of signalized intersections with pre-signals: Theoryand case study". Ph.D. thesis, University of California, Berkeley, 2011
19. Vatalaro, J., &Taylor, R. (2005). Implementing a mixed model Kanban System: The lean Replenishment Technique for pull production. Volume 1, CRC Press.
20. Emde, S., & Boysen, N. (2012a). Optimally locating in-house logistics areas to facilitate jit-supply of mixed-model assembly lines. International Journal of Production Economics, 135(1), 393-402.
21. Hobbs, D.P. (2003). Lean manufacturing implementation: a complete execution manual for any size manufacturer. J. Ross Publishing, Inc., ISBN 1-932159-14-2.
22. Uday Karmarkar, Sunder Kekre,Manufacturing configuration, capacity and mix decisions considering operational costs, Journal of Manufacturing Systems, Volume 6, Issue 4, 1987, Pages 315-324.
23. Liubimov O, Turkin I, Pavlikov V, Volobuyeva L. Agile Software Development Lifecycle and Containerization Technology for CubeSat Command and Data Handling Module Implementation. *Computation*. 2023