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DEVELOPMENT AND SELECTION OF HYBRID DISPATCHING RULE FOR DYNAMIC JOB SHOP SCHEDULING USING MULTI-CRITERIA DECISION MAKING ANALYSIS (MCDMA)

Abstract: *A suitable sequencing and dispatching of jobs on machines is very much essential to improve the performance of any industry. Sequencing is the prioritizing of a set of jobs in a queue based on some decision rule to determine the order in which they will be processed. This paper aims at detailed study and analysis of hybrid rule selection to reduce lead time, waiting time and to increase machine utilization and throughput. In this study four static and eight hybrid dynamic rules were considered and prioritization of jobs is done using TOPSIS algorithm. The hybrid rules are obtained by combining certain dynamic rules. The data includes 47 jobs and 17 machines with different monthly order quantities. Discrete event simulation tool is used for the study and validation of actual data of a manufacturing plant. The results shows that the proposed hybrid dispatching rule, which is a combination of Earliest Creation time (ECT), Shortest waiting time (SWT) and Most work remaining time (MWRT) are very effective in minimizing lead time and maximizing throughput. The another hybrid dispatching rule, which is a combination of Longest Waiting Time (LWT), ECT and MWRT are effective in maximizing the machine utilization.*

Keywords: *Job shop; MCDMA; Priority Dispatching Rule (PDR); TOPSIS; Discrete Event Simulation (DES); ARENA*

1. Introduction

Manufacturing industry plays a significant role in economic development of a country. There is always a need to improve the functioning of these industries. Efforts are being made to address the complex issues that arise every day in manufacturing sector. Job shop relates some such intricate problems as it handles a variety of parts with varying demand. Current study involves improving the overall production process in a job shop handling several components. Any job shop problem involves sequencing and scheduling of incoming parts. Job-shops are classified as static and dynamic based on arrival of jobs for processing. Teymourifar et al, (2018) reviewed that, over the years, researchers has developed many Priority Dispatching Rules which may not be effective in all cases as each of dispatching rule address specific performance measure, which may not be suitable in all practical scenarios as the overall functional effectiveness of the company may depend upon many production parameters such as due date, demand, setup time, machine availability, etc,. Hence, there is need in developing hybrid PDR's which is

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a combination of two or more generic rules or based on the production parameters, depending upon the requirement on the company. The parameters that have much importance in a production environment are chosen by the personnel to develop the PDR that would be more suitable for their company environment.

The problem considered in this study is static in nature. Monthly demands for the jobs are provided as an input to the shop floor. Random arrival of parts and processing times of the jobs are known. Set-up times of the jobs are arrived using the past data. Sequences of the jobs are fixed and jobs are prioritized using priority rules. An initial observation was made to study the overall operational flow of the job shop. Simulation based approach is followed for performance evaluation. A novel hybrid priority rule is developed in this study with a main objective of reducing lead time.

2. Literature Review

The literature review in this chapter examines the work of several researchers on this topic. In recent years, there has been an increasing trend towards integrating the simulation model of a manufacturing system with the shop-floor control system. Computer technology has significantly reduced computation time for evaluating scheduling methods, and now simulation can be used as a tool for real-time evaluation in many circumstances. Simulation can be a part of the real-time, decision-control system of a manufacturing system. It allows the incorporation of dynamic changes on the shop floor into the scheduling function. It also has look-ahead capacities, and it helps to determine the effect of decisions on the future performance of the system. Since the study considers the scheduling of job shop using priority rules, this section majorly covers the background of advancements in modelling the job shop, the priority rules governing the flow of jobs and finally the selection of such priority rules to achieve the desired performance from the system.

2.1. Development of simulation for Job shop scheduling

Job-shop scheduling problem (JSSP) is well-known NP-Hard combinatorial optimization problem. JSSP consists of ‘n’ jobs to be processed on ‘m’ machines the number of possible sequences is extremely large $(n!)^m$ (Rameshkumar & Rajendran, 2018). One of the important methods for analyzing large scale static and dynamic job shop systems is simulation modeling and analysis. Simulation models have recently been used to evaluate the performance measurements of production systems and to identify bottlenecks. Simulation techniques have vastly found its role in industries as they help to design and experience the results of any happening or a scenario of any industry that has materialistic and physical entities interacting within and externally to its surroundings. In recent years, with advancement in computer technology, the computation time needed for carrying out a simulation is significantly lowered thereby leading to a number of applications of simulation in a manufacturing system. Many researchers showed the types and application of simulation in a manufacturing system and its impact on real time decision control (Carrie, 1988). In many studies, attempts were made to implement discrete simulation for governing the shop floor of a production system (Wysk et al., 1994). However, combining the simulation model and the job shop control system always been a difficulty. Real world job shop problem have multiple situations that require to be modeled. These include machine breakdown/failure, power shutdown, operator absentia, operator callousness, etc. As these inputs are dynamic in nature, the following assumptions are made during model creation. The following papers formed the basis of such assumptions. The authors Chan and Chan (2005) and Jahangirian et al. (2010), has done a detailed review of simulation application applications in manufacturing and business processes. Assumptions made during the development of simulation model:

a) Each machine can perform only one operation at a time on any job
b) The processing time and due dates are known in advance
c) The number of jobs and machines are known and fixed
d) Demand is generated at the beginning of every month
e) Processing of jobs are carryout based on their sequence of operation

Kelton et al. (2001) presented some methods and tutorials to develop Arena models along with numerous case studies. A detailed procedure to simulate a single product supply chain model using Arena was proposed by Miranzadeh et al. (2014). Performance improvement in cardiology department of a hospital by simulation (Shriram et al. (In press) Due to intensified global competition and diversified customer demands, industries nowadays need to produce a wide variety of jobs and hence, job shop scheduling become a crucial process in a manufacturing system. A simulation of an actual system serves as an administrator in deciding the task that should be performed next and communicate that information with the system's task implementation software. As a result, attempts to apply simulation models to real-time planning and scheduling started to grow. A Basis for implementing simulation models to real-time planning, scheduling and control was given by Drake et al. (1995). Tunali (1997) proposed a simulation model to study the variation of efficiency of scheduling decisions with the usage of flexible and predetermined process plans under machine breakdown conditions. Chong et al. (2003) provided a simulation mechanism which analyses the past performance and combines various scheduling techniques. Vasudevan et al. (2008) presented a realistic application where in simulation results can be used as an input for scheduling. Here, the generated schedules were used as input for simulation and this method gave a powerful procedure for developing versatile yield enhancement recommendations. Grunder et al. (2013) proposed a simulation model in which they included delivery considerations in a scheduling problem to minimize the total joint cost. Scholz-Reiter et al. (2013) suggested an efficient scheduling procedure by combining shifting bottleneck procedure and variable neighborhood search procedure. A simulation based optimization approach to determine optimal production rate was proposed by Rad et al. (2015). A heuristic approach for priority based job shop scheduling with an objective to minimize make span was proposed by Sandeep et al. (2008). The multi criteria decision making algorithm, Analytic Hierarchy Process (AHP) and job shop modeling were integrated to optimize performance of more than one parameter in one shot and prioritize dispatching rule was presented by Mohanavelu et al. (2017). Soroush (2015) addressed the problem of scheduling jobs on a single processor where the setup times are job-dependent and past-sequence-dependent. He also studied the effect of considering processing time as a linear or convex function of resource assigned and tried to collectively determine the optimum resource allocation. Sathish Kumar et al. (2016) proposed a unique way of modelling job shop using flow metrics in designing layout and machine capacity for overall utilization.

2.2. Study of Dispatching Rules

Priority rules are developed by many researches over the years for finding the ranking order of jobs for processing which are waiting in the queue. Whenever the machine is free, the job which is having the highest priority will be sent for processing. Many scheduling rules were investigated by the researchers. Heuristic rules are developed by combining two or more priority rules. Dynamic rules are implemented by updating the priority ranking with respect to time.

Various priority rules have been studied and analysed by the researchers Holthaus (1997, 1999), Holthaus & Rajendran (1997), Ferrell et al. (2000); Chan, et al. (2003), Jayamohan & Rajendran (2004), Santoro & Mesquita (2008), Vinod and Sridharan (2009), Branke and Pickardt (2011), Pickardt and Branke (2012), Chiang and Fu (2007, 2012), Gupta & Starr (2014), Xiong et al. (2017)) and most of them have achieved good performance for the problems considered in their study.

The growth in application of simulation models to job shop scheduling, the incorporation of dispatching or priority rules into such models also started to grow. Application of such dispatching rules to job shop scheduling problems started in early 90's (Kim & Bobrowski, 1994). Scheduling through priority rules become one of the most effective method. Baykasoğlu and Özbakır (2010) studied the impact of priority rules on performance of scheduling different job shops. A case study based on usage of real-time priority rules on simulation modeling and analysis for scheduling made by Krishnan et al. (2012) studied the performance of a flexible manufacturing system with machine breakdown and compared without breakdown using various priority rules. The data mining technique to prioritize dispatching rule for a job shop scheduling problem (Shahzad & Mebarki, 2012). The influence of dispatching rules on average production lead time for multistage production systems was analyzed by Hubl et al. (2013). Chen and Matis, (2013) developed a priority rule named as the weight biased modified rule that minimized the average tardiness of jobs in a multiple machine job shop.

Many researchers have developed heuristics based on the factors that they have found as important in scheduling. Some of them would be suitable only for specific problem types as any scheduling environment would be subject to many constraints and assumptions. Also, the process flow would be different for various practical scenarios based on the incoming job types, available resources, processes to be underwent by the jobs etc.

2.3. Integration of MCDM algorithm with job shop simulation models

Many Multi Criteria Decision Making (MCDM) approaches are proposed over the years for a variety of decision making problems. As the researchers realized the importance of dispatching rules on job shop scheduling, a few started using decision making tools to identify the best priority rules from the available set of rules. One such study was done by El Bouri and Amin, (2015) in which they combined an ordered weighted averaging technique and data envelopment analysis model and used it to identify the best priority rule in a flow shop environment. Kusi-Sarpong et al. (2018), was presented supplier selection and evaluation using multi criteria approach. Integrated approach to multi criteria discussion making for product development was discussed by Soota (2014). TOPSIS is used for group decision making studied by Shih et al., 2007. The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is a powerful technique compare to other MCDM developed by Hwang and Yoon (1981). This method is simple and intuitive, but it enables systematic and consistent aggregation of the criteria. It is used for obtaining alternate solutions by determining the distance from Positive Ideal Solution (PIS) and the Negative Ideal Solution (NIS) (Kim et al., 1997). However, no attempt was made to use to TOPSIS in selecting the most efficient priority rules that is specifically applicable to a particular manufacturing system. Sequencing the jobs and determining the performance measures using simulation techniques have been one of the most effective measures to compare the effectiveness of each PDR's used.

From the literature, it is understood that researchers have been continuously working on improving the overall performance of the job shop using simulation models and priority rules, and yet there has not been an optimal method as appropriate priority rule has not been selected. This is mainly because of the complexity involved in the structure of each job shop. For instance, in case of a dynamic job shop, static priority rules do not work effectively. The main aim of the research is to reveal an effective heuristic method combining the static and dynamic priority rules, that can be used for scheduling in a job shop environment. In this paper, one such attempt was made by using TOPSIS algorithm to select the most useful hybrid dispatching rule and to study its effect on the output of the system. The priority rules selected using the TOPSIS method is stochastic in nature, as it is heavily influenced by the demanded performance (machine utilization/throughput/waiting time) metric and the nature of job shop. Hence, by this method a uniform platform for selecting the priority rule is created wherein different performance metrices and nature of job shops can be handled effectively.

3. Problem Definition

The current sequencing method used in the plant is being done manually, based on due date without considering the waiting time of jobs and machine utilization. This paper aims at monitoring performance parameters to control the job shop sequencing and scheduling. This problem is dealt with development of hybrid rule based on the requirement to match up the job shop performance.

3.1. Objectives

After a detailed literature study on the current researches done in this area and based on the job shop condition, the following objectives were formulated:

- To develop a Discrete Event Simulation (DES) model of the job shop and extract job shop performance evaluation parameters namely, throughput, queue statistics, lead time and machine utilization based on static dispatching rules available.
- To formulate hybrid dispatching rules and effectively prioritize them using TOPSIS algorithm.
- To obtain job shop performance evaluation parameters based on prioritized hybrid dispatching rule and compare the results with existing static and dynamic rules.

4. Methodology

The study aims at refining the overall scheduling process of a job shop environment. In order to evaluate the success of the work, the study was designed as a case study in an automotive industry.

Step:1 Data collection for developing a hybrid dispatching rule in a job shop
Step:2 Developing a TOPSIS algorithm for dispatching rule selection
Step:3 Data collection for building a simulation model
Step:4 Developing a simulation model and evaluate performance measures
Step:5 Evaluate and compare the performance measures of the system results
Step:6 Implementation in the real-time scenario.

4.1. Data collection for developing a hybrid dispatching rule in a job shop

Computerized scheduling techniques made a tremendous impact on minimizing the cost of operation and optimizing the structure of complicated manufacturing systems. A scheduling system always aims to convert customer needs into scheduled operations effectively and as a result in most cases there are multiple objectives in a scheduling problem. The allocation of resources in order to meet the objectives within the constraints laid by the operational environment is a very difficult process.

A job shop scheduling problem (JSSP) is briefly described below, The problem is represented by a 3-tuple, say $S = \{M; J; C\}$

Where, $M = \{M_1, M_2, \ldots, M_m\}$, represents the machines, $J = \{J_1, J_2, \ldots J_j\}$,represents the jobs and $C = \{C_1, C_2, \ldots C_c\}$, represents the problem constraints. For every job, $J_i = \{\{Op_{i1}, \ldots,$

$Op_{im}\}$, at_i, dd_i; $w_i\}$, there exists a set of operations Op_{ij} .Each operation is specified by a specific set of parameters namely the processing time on every machine, inter-arrival time of the jobs at_i, job due date dd_i, weight function for the job w_i, and an operational sequence. The arrival time and due date are two important parameters that specify the start time and end time of processing on a job. The weight function for each job is a representation of the relative importance of the job in the scheduling process.

The object of a JSSP is to develop an ordered sequence of operations to optimize the output. The basic difference between a job shop and a dynamic job shop is that, in a dynamic job shop, there is a continuous arrival of jobs in the production line. In any job shop, scheduling is done in accordance with several sets of jobs that are assigned to be processed in several different of machines for a specific period of time to achieve the anticipated target. In this paper, four performance parameters namely, due date, cycle time, production volume, queue time are chosen. The performance of a dynamic job shop varies in phase with the order of job arrival which eventually depends on due date and production volume. The flow of job is completely controlled using these parameters and TOPSIS algorithm. This algorithm is used to select the dispatching rule. The job shop can be optimized using the utilization of machines in each machining center. Based on the results the surplus machines can be removed or if it falls in the category of deficit, few more machines need to be added to the existing ones.

4.1.1. Development of hybrid dispatching rule

There are numerous methods for job prioritization and scheduling which ranges from direct manual methods like Gantt charts to advanced computer aided techniques. One such technique for job prioritization is the use of priority sequencing rule. The priority rules, also called dispatching or scheduling rules, are widely used to provide good and time-efficient solutions to job-shop scheduling problems for decades. In a manufacturing system, scheduling through priority rules is one of the well-known methods. Thus proper selection and prioritization of dispatching rule results in better production planning. Any job shop has two categories of dispatching rules are static rules and dynamic rules. Static rules are those rules in which the job priorities are time invariant whereas the dynamic rules vary with the passage of time. One major advantage of this technique is its ability to incorporate real time information on the operating conditions into the schedule. Some standard priority rules include first in first out (FIFO), last in first out (LIFO), earliest due date (EDD). Besides these standard rules, there are certain specific priority rules like critical ratio (CR), Shortest processing time (SPT), slack per remaining operations(S/RO) etc. For a job, Critical ratio is defined as the ratio of time remaining to attain due date to total work time remaining. In CR rule, if the critical ratio of a job is less than one then it implies that the job is behind schedule and is given higher priority and if the critical ratio of a job is more than one then it is ahead of schedule and can afford to wait. In case of SPT rule, the job with the shortest processing is given highest priority. For a job, like CR, slack is another parameter which is the difference between time remaining to attain due date and total work remaining time. In S/RO rule, the slack of a job is divided by number of operations remaining to obtain a ratio called slack per remaining operations and that job with least S/RO is given the highest priority.

Though these seem to be simple, the actual task of scheduling becomes really difficult with a large number of jobs and thereby requires a number of other parameters for finding out an optimum schedule. These parameters include arrival time, due date, setup time, processing time, waiting time, creation time, work remaining time, number of machines available etc. Based on these input, the scheduler or the software uses the dispatching rules to prioritize and to find out an optimal job schedule.

In this paper, Job sequences are not generated based on any scientific approach in the shop floor considered. Sequencing of parts are carried out based on experience of the decision maker using a multi criteria decision making algorithm (TOPSIS) for prioritizing dispatching rules in a dynamic job shop. The rules are based on creation time, work remaining time, waiting time and considering earliest creation time, longest creation time and the same way for rest of the rules. By combining these six rules, several hybrid rules are obtained. Each rule is chosen with the solution obtained by the usage of TOPSIS algorithm. The ideal solution varies based on the requirements thereby choosing the dispatching rule.

According to TOPSIS rule weights are given to each performance parameter. The weights depend on current dynamic situation of job shop. If the production volume is not met for a particular period the hybrid rule can be changed until the target is met. Rules that are considered in this paper are listed in table 1.

Table1. Dispatching Rules

Static Rules	Dynamic Rules	Combined Hybrid Rule
FIFO- First in First Out LIFO- Last in First Out SPT- Shortest Processing Time LPT- Longest Processing Time	ECT - Earliest Creation Time LCT - Longest Creation Time SWT - Shortest Waiting Time LWT – Longest Waiting Time LWRT- Least Work Remaining Time MWRT-Most Work Remaining Time	ESM - ECT+SWT+MWRT ELM - ECT+LWT+MWRT ELL - ECT+LWT+LWRT ESL - ECT+SWT+LWRT LLL - LCT+LWT+LWRT LLM - LCT+LWT+MWRT LSL - LCT+SWT+LWRT LSM - LCT+SWT+MWRT

4.2. Applying TOPSIS (Technique for Order Preferences by Similarity to the Ideal Solution) algorithm for dispatching rule selection

TOPSIS is a multi-criteria decision making (MCDM) algorithm developed by Hwang and Yoon (1981), which is often used to prioritize and select evaluating parameters. The fundamental principle behind this algorithm is that the picked alternative must have the minimum deviation from what is an ideal solution and the maximum deviation from the negative-ideal solution. This study comes with selecting the best rule for getting desired outputs from chosen optimizing parameters. During the process of optimizing the job shop four attributes namely due date, production volume, queue time and cycle time were taken. The weights for the respective attribute were allocated based on the dynamic situation of job shop. Based on the input data, normalized value is obtained for all attributes was found out. Then the weighted standardized matrix was obtained by multiplying standardized matrix with their respective weights.

Step 1: An Evaluation matrix is framed based on the number of available alternatives and criteria. Here, the various alternatives are the 47 different types of jobs available and the different criteria are due date, production volume, cycle time, queue time.

Step 2: The evaluation matrix is then normalized to form standard decision matrix.

$$e_{ab} = \frac{E_{ab}}{\sqrt{\sum_{a=1}^{4} E_{ab}^2}}$$

where a=1, 2, 3, 4. b=1, 2, 3…..47.

Step 3: Weighted decision matrix is formed by multiplying the given weights for each criteria with the respective rows of standard decision matrix.

$$W_{ab} = w_a * e_{ab}$$

where w_a is the weight given to each criteria a=1,2,3,4.

Step 4: Based on the type of rule the ideal solution (is_a) and negative solution (ns_a) is chosen. Then, ideal solution matrix is framed based on ideal solution for each criteria.

$$IS_{ab} = \sqrt{(W_{ab} - IS_a)^2}$$

Similarly, negative solution matrix is also obtained.

$$NS_{ab} = \sqrt{(W_{ab} - NS_a)^2}$$

Step 5: Solution vectors are obtained for each alternative job

$$IS_b = \sqrt{\sum_{b=1}^{47} IS_{ab}^2}$$

where IS_b is the ideal solution vector.

$$NS_b = \sqrt{\sum_{b=1}^{47} NS_{ab}^2}$$

where NS_b is the negative solution vector.

Step 6: The deviation from ideal solution is calculated.

$$\frac{NS_b}{IS_b + NS_b}$$

The figure 1 shows the flowchart of steps followed for applying TOPSIS algorithm to any system.

After formulation of hybrid dispatching rule, the TOPSIS algorithm is applied to get the preference order. The distinguishing between different rules was brought out by deciding the ideal solution and negative solution. For instance, the ideal solution for earliest creation time will become the negative solution for longest creation time. Similarly for other rules the ideal solution play a critical role is deciding the order of preference. In a nutshell, when TOPSIS algorithm is compared with direct weighting it is not that accurate. However, best results can be obtained by using accurate weights in this method but as the size of evaluation matrix tends to infinity, accuracy seems to reduce. In this study, positive results are obtained even though the model dealt with 4 criteria and 47 alternatives.

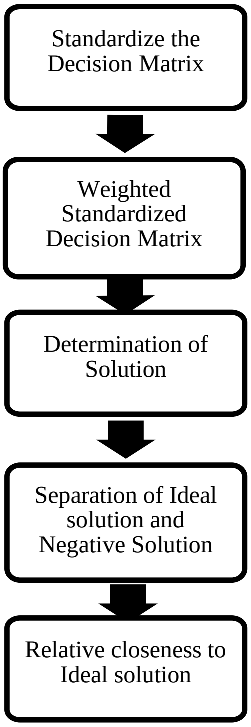

Figure 1. Steps followed for applying TOPSIS Algorithm.

4.3. Data collection for simulation model building

For this study, real time data were acquired from a manufacturing industry. The table 2 given below gives the total production volume, mathematical expression for inter arrival time and sequence in which jobs to be machined, where 'G' indicates group of machines, due date in days, cycle time and setup time in minutes. In Arena simulation software, input analyzer is the tool used to obtain the probability distribution for routing of parts to the respective machines. By using this tool a range of possible expressions can be obtained and from those possible expressions the best choice can be fed to the model. The various groups of machines such as milling machine and turning machine centre along with their function are shown in the below listed table 3.

Table 2. Production Order

S.No	Quantity	Expression	Sequence	Due Date (Days)	Cycle Time (Min)	Setup Time (Min)
1	15096	139 + 90 * BETA(0.82, 0.568)	G6, G1	7	16.09	5.2
2	130240	UNIF(4.08e+003, 5.26e+003)	G1	5	1.2	2.3
3	150	POIS(107)	G1	16	15.84	5.4
4	150	NORM(3.01e+003, 100)	G1	8	15.84	6.4
5	650	101 + LOGN(22.7, 58.2)	G1	10	5.94	3.5
6	300	14.5 + 13*BETA(0.865, 0.708)	G1, G1, G1	14	9.5	4.5
7	12000	8.46e+003+1.09e+003 * BETA(0.872, 0.4)	G2,G1	15	1.08	5.3
8	4500	1.6e+003 + GAMM(161, 0.46)	G6	18	9.5	6.2
9	900	POIS(152)	G1,G1	20	9.5	9.5
10	45646	1.21e+003+179 * BETA(0.426, 0.571)	G1	6	1.57	4
11	100	POIS(160)	G1	29	1.18	7.5
12	100	455 + 65 * BETA(0.695, 0.47)	G1	24	6.65	5.5
13	12340	UNIF(1.94e+003, 4.59e+003)	G1	30	3.82	6.2
14	100	UNIF(614, 937)	G6	28	13.39	7.8
15	800	TRIA(2000,2424,3500)	G3,G6, G6	4	11.91	5
16	16300	UNIF(400,500)	G5,G6	8	11.91	6.4
17	400	POIS(564)	G3	6	4.75	7.5
18	900	UNIF(300,600)	G3,G6, G6	9	19.8	8.5
19	2835	POIS(1050)	G4,G6	9	3.21	8.4
20	14320	513 + WEIB(63.4, 0.666)	G5	8	3.21	9.5
21	8745	POIS(180)	G5	13	13.35	6.5
22	8410	307 + WEIB(50.2, 2.07)	G5	14	13.35	4
23	16640	307 + WEIB(46.4, 1.72)	G2,G2, G2,G5	14	3.17	6.9
24	9600	3.08e+003 + EXPO(144)	G5	15	4.98	7.8
25	300	464 + 671 * BETA(0.396, 0.345)	G6,G1	16	4.98	6.8
26	750	1.4e+003 + EXPO(253)	G1	17	4.98	5.6
27	13299	UNIF(340, 695)	G3	25	4.98	4.3
28	520	TRIA(35.5, 88, 127)	G3	19	9.8	2.6
29	5300	POIS(50)	G3,G3	20	4.98	7.8
30	200	UNIF(284,321)	G5	21	4.98	8.9
31	960	POIS(355)	G5,G1	23	1.2	8
32	3940	POIS(170)	G2	24	1.2	9.2
33	2150	64.5 + ERLA(36.4, 1)	G2,G2	25	1.2	9
34	57872	UNIF(90, 110)	G2	26	1.2	6.5
35	2880	7.5 + 49 * BETA(0.84, 0.63)	G2	15	16.49	3.5
36	2879	TRIA(35.5, 91, 127)	G2,G2,G2	3	16.49	4
37	300	UNIF(43, 82)	G2,G2,G2	29	1.2	5.2
38	1000	TRIA(32.5, 89, 122)	G2	30	1.2	8

Table 2. Production Order (continued)

S.No	Quantity	Expression	Sequence	Due Date (Days)	Cycle Time (Min)	Setup Time (Min)
39	5600	UNIF(55, 243)	G2	16	7.56	8.4
40	8520	5.81e+003+1.69e+003*BETA (0.581,0.469)	G2	15	9.49	7.5
41	14220	849+ EXPO(167)	G2	15	9.49	6.3
42	480	842 + EXPO(167)	G2,G2	4	59.42	9.2
43	500	UNIF(43, 241)	G5,G6,G4	5	59.42	8.4
44	3380	UNIF(157, 318)	G4	12	59.42	4.5
45	700	149 + 94 * BETA(0.293, 0.341)	G4,G6	13	9.47	6.5
46	3380	3.08e+003 + EXPO(144)	G6	11	7.56	4.5
47	750	UNIF(1.36e+004, 1.51e+004)	G4	5	1.08	5.5

Table 3. Machine Groups and their Functionality

Group	Functionality	Machines
1	Only Turning	TC 01, TC 02, TC 03, TC 04
2	Turn Mill Centre	TMC 05, TMC 06
3	5 axis Machines	VMC 08, VMC 12
4	Only bed Operations	VMC 09, VMC 11
5	Large Bed Height	VMC 01, VMC 02, VMC 04, VMC 05
6	Small Bed Height	VMC 03, VMC 06, VMC 07

*VMC- vertical milling center, TC-turning center, TMC- turn mill center.

4.4. Development of Simulation model of a shop floor

Modeling and simulation is one of the key parts of optimizing dynamic job shop. It helps in replicating the real dynamic situation of the job shop. The system behavior can be predicted using mathematical modeling representing the real systems. The framework of simulation process shown in the figure 2. The Simulation model is developed for 47 part types. An order can have one or more than one part that must be manufactured, while the quantity of each part that must be manufactured can also differ. Each part has to go through several different operations during manufacturing. These operations are performed on specific machines, depending on the type of operation. The operations of a part follow a certain sequence and no two operations can be processed at the same time.

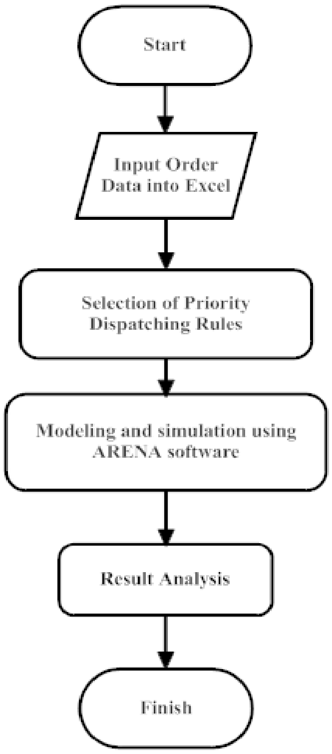

Figure 2. Framework of simulation process

Figure 3 shows a typical Entity structure. The order has 'n' number of different types of parts, for example Part 1 requires four operations and Part 2 only two operations. The operations length varies from two to five operations.

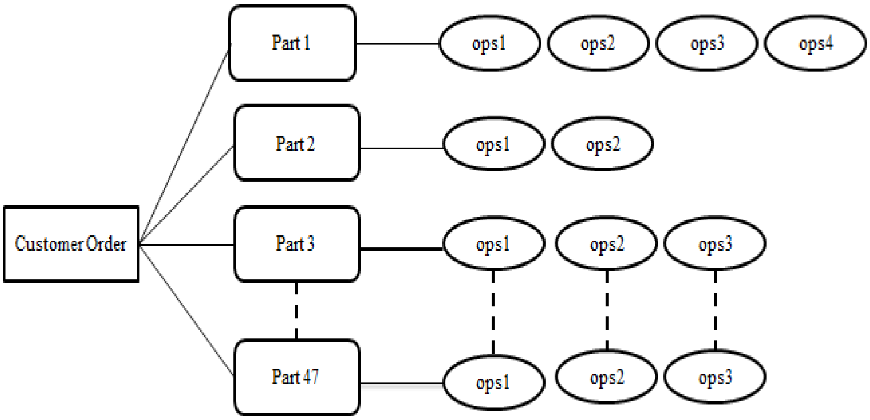

Figure 3. Entity Structure

In this paper the modeling software ARENA is chosen for simulating shop floor as shown in figure 4. The modules are created based on the inputs fields like job inter-arrival time and the order in which the job is made to arrive at the machine. The inter arrival time is represented as a mathematical distribution based on the data acquired from job shop. The order is based the weights chosen for each optimizing parameter in TOPSIS algorithm. The rank of each job is assigned and least attribute value is chosen as determining parameter. The max arrival of job was based on the demand for that complete simulation time.

The machines are modeled and similar machines are put under one station for instance, the two milling machines are under one roof of milling center. This is done so that when a job arrives for machining in a particular station of machines the job is processed in which ever machine is idle. By this method the waiting time can be eliminated as they are not directed to a particular machine.

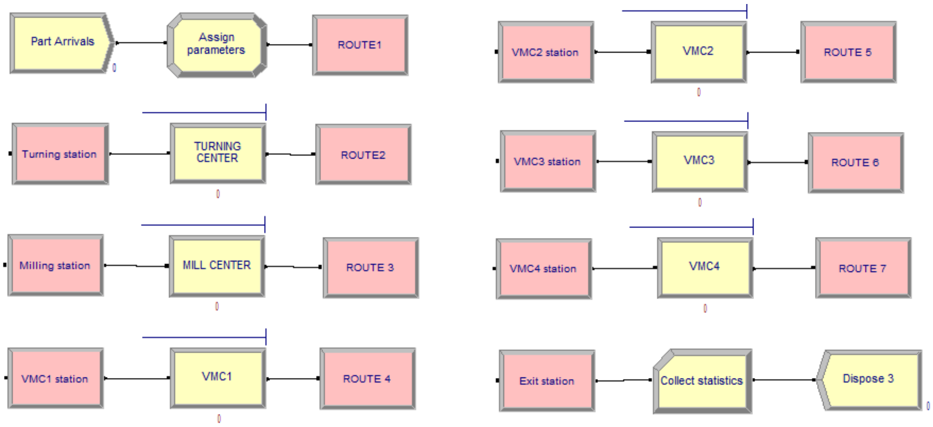

Figure 4. Job shop- Arena Model

The wait time minimization is one the key goals to be achieved finally at the end of optimization. Furthermore, the routing of jobs is done based on the sequence order of machine. During this process the transfer time is neglected as it got very less influence on the system performance. The simulation time was for one month and the replications were varied from two to five and the results were analyzed. The 3D layout of simulation as shown in the figure 5.

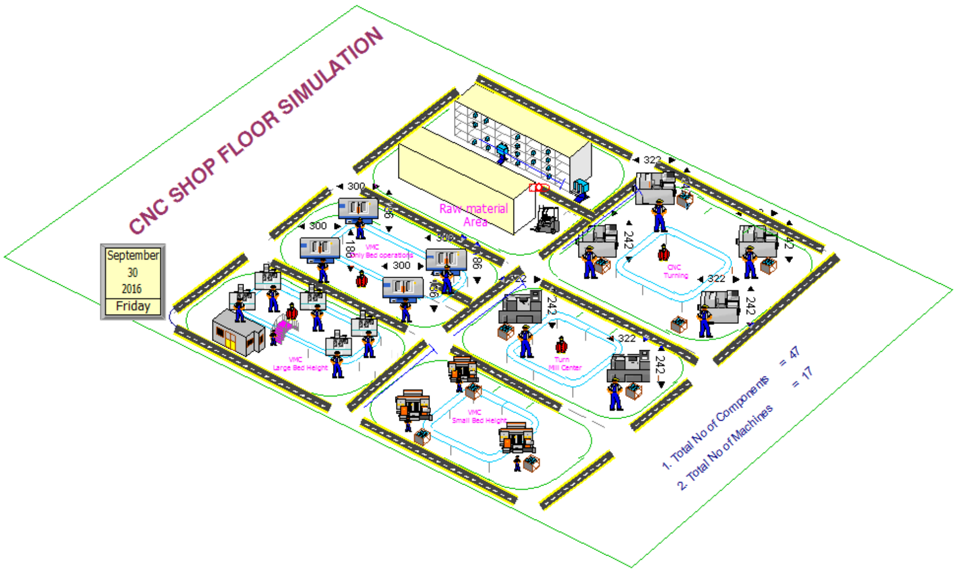

Figure 5. Layout of job shop floor

4.5. Simulation Results

The job shop modeled in Arena was simulated for duration of one month with ten replications and results output are given in graphical forms in the figures. For studying the performance of the system under various dispatching rules the following parameters were considered which includes average total number of throughput, wait time and machine utilization. The total number of components produced for a period of one month as shown in the figure 6.

It can be seen from the figure that the hybrid rule ESM gives the highest number of throughput. ESM is a hybrid rule combining three dynamic rules namely earliest creation time, shortest wait time, and most work remaining time. By comparing two hybrid rules say ESM and LSL; in determining the throughput performance, the ideal solution selection plays a vital role. For instance, the criteria creation time and production volume are given much higher priority in ESM but in LSL hybrid rule, the jobs with less production volume are given higher priority as least work remaining time is to be achieved. For given creation time and queue time the work remaining time is directly proportional to the production volume. Hence with ESM hybrid rule much throughput is achieved. The performance with hybrid rule LSM is better than LSL as most work remaining time yields more production volume as in both the rules longest creation time is chosen. The hybrid rule LLM combining longest creation time, longest wait time and most Work remaining time produces results close to the highest number out which is considerably high when compared to static rules like Shortest processing time, last in first out etc.

The following figure 7 shows wait time of entities when operated under various dispatching rules. The hybrid rule ELM and ESM turns out to be best rule for minimizing wait time. By considering the overall performance of the rules with respect to number out and wait time ESM hybrid rule proves better.

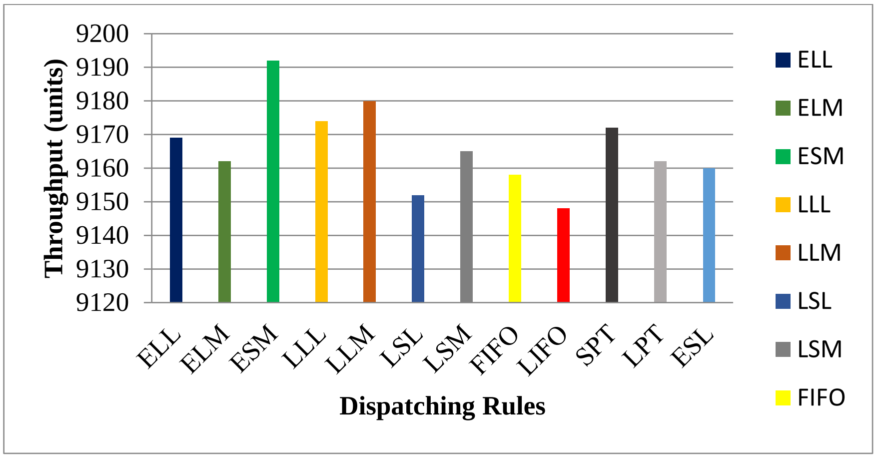

Figure 6. Throughput Vs. dispatching rules

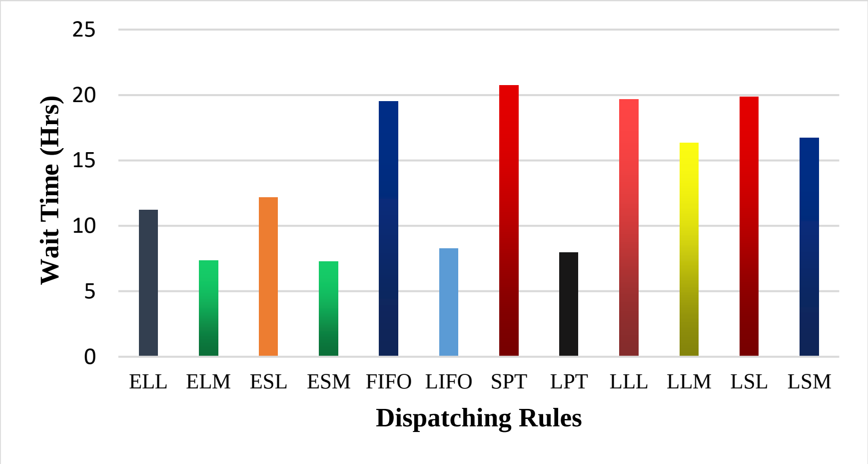

Figure 7. Wait time Vs. dispatching rules

From the figure.8, the lead time variation with different dispatching rules are studied. It is evident that, overall lead time is reduced with using the hybrid rule ESM (ECT+SWT+MWRT). Currently, job prioritization is done based on SPT (static rule) rule in the company and it was observed that lead time for processing 47 jobs are nearly 32 days. The lead time for processing all jobs are nearly 30 days using ESM rule. There is saving of 2 days in lead time is achieved compare to other rules.

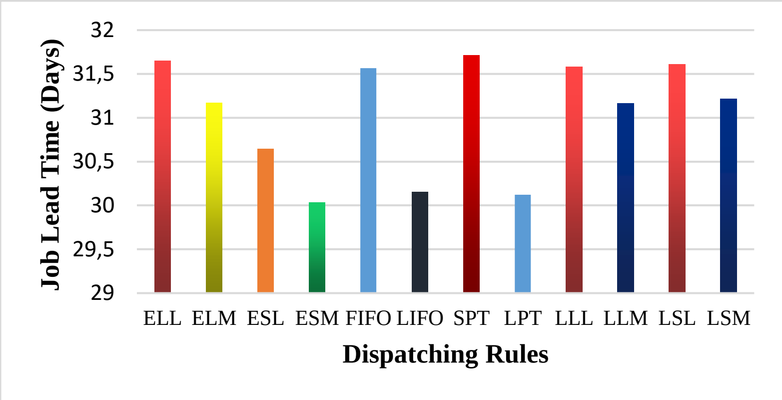

Figure 8. Job Lead time Vs. dispatching rules

The average machine utilization of all 17 machines under various rules were obtained. Based on this the machine having the maximum machine utilization was chosen from each machining centers namely milling center, turning center and vertical milling center. Now the variation of machine utilization with different dispatching rules were plotted and shown in figure 9 from which it can be inferred that the hybrid rules ELM shows the better result were compared to other rules.

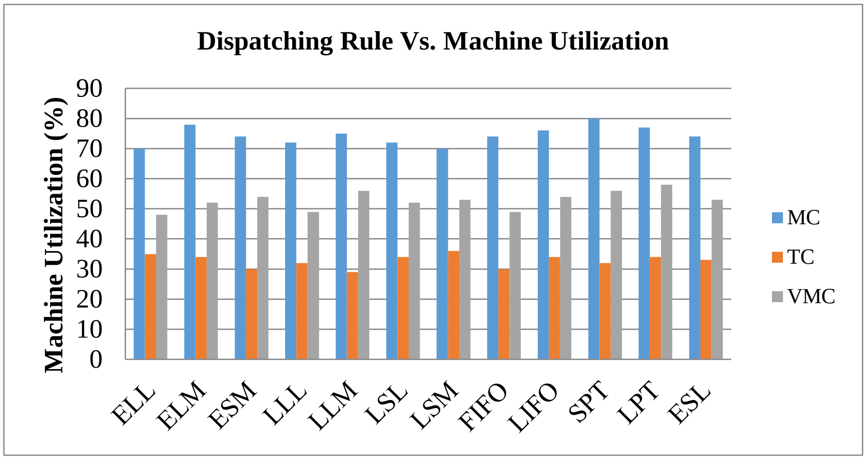

Figure 9. Machine Utilization vs. Dispatching rules.

5. Conclusion

A detailed study has been made at auto ancillary with an objective of developing a priority rule for scheduling the jobs to improve the performance of the shop floor. Grouping of machines was carried out based on capacity and functionality of the machines. Grouping of machines is found to be very effective in handling large number part varieties. Based on various static and dynamic rules, hybrid dispatch rules were framed. Job prioritization was done using TOPSIS algorithm in accordance with the constraints laid by the framed dispatch rules. A Simulation model of the shop floor was developed using Arena simulation software based on the real data. The simulation model developed helps in identifying the bottlenecks in the shop floor and also in evaluation of various performance measures of the system. The effect of these hybrid rules on the performance of the system was analyzed using three output parameters namely throughput, waiting time and machine utilization. Based the analysis, it was found that the ESM hybrid rule proves to be improving the overall performance of job shop as it collectively satisfies maximum production, minimum waiting time and highest machine utilization for two machining centers. The simulation was run based on ESM rule to identify machines with minimal machine utilization. The surplus machines in each machining centers were removed during successive simulations and was found out that there was not much impact on the throughput thereby providing a chance for Shop floor resource optimization. Through real time data acquisition and analysis, dynamic job prioritization can be done to attain optimal productivity with minimal resources. Further study can be done on the integration of machine learning tools like artificial neural network and TOPSIS to create a system that can prioritize jobs based on the available input and required output conditions without human intervention to optimize productivity.

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