International Journal of Engineering Research and Development
e-ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 11, Issue 11 (November 2015), PP.75-81

Multi-Level Dynamic Job Sorting for Increasing Productivity Using Discrete Event Simulation (Diverging Conveyors)

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Abstract:- The advancement in the computer technologies and its integration with the production system, the production system has become highly flexible producing large family of products. One of the main objectives of flexibility is to reduce the setup cost and time to respond to the market demands. Even the most flexible system may invite some setup cost in job changes, so it is often desirable to change the sequence of jobs to further reduce the setup cost and its related time. In this paper the influence of dynamic job sequencing on a diverging junction conveyor production line with the objective to save the production cost & time have been presented. A production line which produces different batches of jobs is considered, where the raw part of different jobs arrive from the source randomly. Each batch of job has to undergo different processing operations. A production line is modelled and simulated using various production elements and its influence on the setup cost & time is studied and presented. The object oriented, discrete event simulation software is used to model and simulate the production system.

Keywords:- Diverging Conveyors, Sorters, Dynamic Sequencing, Discrete Event Simulation, reduce makespan, production time saving.

I. INTRODUCTION

Information technology and computerized automation have significantly improved flexibility in recent manufacturing. Today, most high-volume manufacturing systems may appear to be old shaped transfer lines but in fact they have become highly flexible, producing a large family of products such as electronics, automobiles, and other consumer goods. One purpose of striving for flexibility is to reduce the setup cost or time-to-respond to the growing diversity of customer demands. However, even the most flexible systems may still invite some setup cost in job changes. It is often advantageous to change the job sequence to further decrease the setup cost and time.

The research on scheduling in the vehicle industry has mainly been focused on the car sequencing problem, which was first described by Parrello etal. (1986)[1]. Enumerative approaches, such as the branch-and-bound algorithm of Carlierand Pinson (1989)[2], can only conquer small-scale problem instances. The most common heuristic methods devised in the early days include dispatching rules (Sculli, 1980; GreenandAppel, 1981; Kanet andHayya, 1982; Baker, 1984) [3], [4], [5], [6] and shifting bottleneck (Adams et al., 1988; Holtsclaw andUzsoy, 1996; Balas and Vazacopoulos, 1998; Liu andKozan, 2012) [7], [8], [9], [10].

Bianco, Dellolmo, Giordani, and Speranza (1999) [11] have minimized the makespan in a multimode multiprocessor shop scheduling problem. Each task can be undertaken by any methods in a set of predefined alternative modes, where each mode specifies a required set of assigned processors and a processing time. At any point of time, each processor can be used at most by only a single task.

Akpan (1996) [12] has introduced a network technique that is a very useful tool for analysis of job shop sequencing problems. This technique offers a basis for finding an optimum solution. In this technique, the jobs priority on machines is determined by FCFS (First Come, First Serve) rule. Guinet (2000) [13] has proposed a procedure for solving job shop scheduling problems. In this procedure, the objective is to minimize the maximum completion time of jobs. Lee, Piramuthu, and Tsai (1997) [14] have proposed to combine capabilities of genetic algorithms and machine learning techniques in order to develop a job shop scheduling system. Blazewicz, Domschke, and Pesch (1996) [15] have presented an overview of solution techniques for solving job shop problems. After a brief roundup of all the trends and techniques, they concentrated on branching strategies and approximation algorithms belonging to a class of opportunistic and local search scheduling.

Sabuncuoglu and Bayiz (2000) [16] have studied reactive scheduling problems in a stochastic manufacturing environment. An active schedule has the property that no operation can be started earlier without delaying another job. Specifically they have tested several scheduling policies under machine breakdowns in a classical job shop system. In their researches, the performance of the system is measured for the mean tardiness and makespan criteria.

Yu and Liang (2001) [17] have presented a hybrid approach combining neural networks and genetic algorithms to solve the expanded job shop scheduling problem. Satake, Morikawa, Takahashi, and Nakamura (1999)[18] have proposed a simulated annealing method based on the rescheduling activity of the human scheduler in order to void local search solution for solving job shop scheduling.

Shiqing Yao,ZhibinJiang n, NaLi(2011) [20] have presented A branch and bound algorithm for minimizing total completion time on a single batch machine with incompatible job families and dynamic arrival. A flexible dispatching rule for minimizing tardiness in job shop scheduling were presented by Binchao Chen, Timothy I. Matis(2013) [21]. Rui Zhang, Pei-ChannChang, ChengWuc (2013)[22] presented A hybrid genetic algorithm for the job shop scheduling problem with practical considerations for manufacturing costs. Xinchang Haoa, Lin Linb, Mitsuo Genc, Katsuhisa Ohnoe, (2013)[23] presented Effective Estimation of Distribution Algorithm for Stochastic Job Shop Scheduling Problem.

Andrea Rossi (2014) [24] studied Flexible job shop scheduling with sequence-dependent setup and transportation times by ant colony with reinforced pheromone relationships. K. Li, J.Y.-T. Leunga, B. Y. Cheng (2014) [25] presented an agent-based intelligent algorithm for uniform machine scheduling to minimize total completion time. Wenchang Luo, Min Jib, (2015) [26] presented Scheduling a variable maintenance and linear deteriorating jobs on a single machine with a goal to minimise the makespan and total completion time.

II. METHODOLOGY

A. Tools used to build the model

The simulation of production line is modelled using the Tecnomatix Plant Simulation software. Tecnomatix is an object oriented GUI based discrete event simulation software that supports objective decisions by dynamic analysis, to enable users to safely plan and, in the end, to reduce cost.

The objects that are used to build the model and, its function are as described.

Source: The source is a place which produces the parts.

Line: The conveyor is modeled as a line in the model on which the parts are transported.

Flow Control: The transportation of the part to its corresponding workstations as per the batch is coordinated by the flow control tool.

Single Pro: It is a processing station in which the parts undergo some processing operations. In our model stations are modeled using Single Pro.

Turn Table: It is a rotating platform which moves the part to the required destinations.

Buffer (Sorter): A buffer is a production element which stores the parts temperiorly when the component following it in sequence of stations fail and also it moves parts on, when the preceding components stop working, preventing the production process from grinding to a halt. The exit sequence of the buffer can be defined in which the parts exit based on the sorting criteria defined where the sequencing of the parts can be changed.

Robot: A pick-and-place robot is used in the production line which picks a part up at one station, rotates to another station, and places it there.

Drain: It is place where the batches of parts are collected.

B. Problem Statement

In this paper three layout of the production line is modelled to study the influence of the production elements like buffer and robot. The first layout is semi-automated model without the storage element and material handling equipments. The transfers of the job through successive stations are transported by conveyors and loading of the parts are done manually from conveyor to station (station to conveyor). The second layout is also a semi-automated layout where, the buffers are used and jobs are transported by conveyors and before entering the station it is stored in buffer and accessed by the station based on the sorting criteria defined in exit strategy of buffer. The third layout is fully automated layout the jobs are Loaded/Unloaded to the station by the pick and place robot. The layout of the 3 production line is shown in the Fig.1, Fig.2 & Fig.3.

C. Operation and Processing Time of Jobs

There are 10 batches of jobs to be produced in the production layout the raw part of each batch arrive randomly from a source and are processed at its respective processing station. The processing routes of each job to the respective station are shown in the table 1. Time taken for processing each job in processing station and setup time taken for each job is given in the table 2.

D. Sequencing of Job in Buffer

Once the jobs enter the buffer of respective station the job that is loaded into station is based on the sorting criteria defined at the exit point of the buffer. Two sorting criteria are defined in the buffer first one is similar criteria, this criteria search for similar jobs in the buffer storage and loads the same job next to the station. E.g.: if job1 is already loaded into machine after the processing of job1 in the processing station the buffer search for job1 in the buffer racks and loads it. The second criteria defined is based on similar route operation, that is same route jobs are preferred next to the processing station if similar jobs are not available. E.g.: if job1 is loaded into the station1, the buffer searches for job1 in the buffer racks, and if job1 is not present in the racks similar route job are preferred next. The table 3 shows the sequencing done in station 1 based on the criteria defined. Referring to the table 3 job1 and job3 are having same route and hence are preferred next.

E. Types of Distribution used in the model

Manufacturing environment is highly socastic in nature there are various probality distributions used to predict the randomness in manufacturing systems. The jobs arrive from the source randomly into the production line having different processing operations.The arrival of the jobs from the source is modelled as poission distributions with □=5, The parameter λ designates the average number of events taking place in one unit of time. The distribution is given by

$$f(k) = \frac{\Lambda^k}{k!} \exp(-\Lambda)$$

The jobs arrive from the source randomly into to the production line, for modelling random arrival for queuing model Poisson distribution is used [19]. The service time and setup time is modelled as a erlang distribution for each processing station because the Erlang distribution is used to model the time to complete *n* operations in series, where each operation requires an exponential period of time to complete[19]. The distribution is given by

$$f(x) = \frac{1}{\beta} * \frac{\frac{x}{\beta}^{k-1}}{k-1!} * \exp\left(-\frac{x}{\beta}\right)$$

The standard deviation for setup time for each station when job arrives and its machining time on each station for each job with its range, lower and upper bound is given in the table 6 and 7.

III. RESULTS

A. Simulation Times of Different Production line

The total simulation time for producing 150 batches of parts in three models is shown in the table 4.

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B. Percentage of Machine Utilization

It is observed that, with the use of production elements like buffer and robot the machine can be utilized effectively and its percentage of usage can be increased. With the increase in the utilization of machine the overall simulation time is reduced.

C. Influence of Storage in the Layout

The above layout is designed with a storage capacity of 10 parts. The effect of increasing the capacity of the buffer is studied. To examine the effect of increase in the capacity we consider the layout 3 and its capacity is increased to 20 & 30, its effect on total simulation and utilization of machine is shown in Table 5 below.

From the table 5 it is observed that, the total simulation with the increase in the storage of the racks is almost same. Hence with increase in the storage the total time in production is not reduced. However there exists a optimum buffer capacity that reduces the work in process inventory.

IV. CONCLUSIONS

Simulation of a diverging conveyor junction production line, studying the influence of the production elements like buffers and sorter with the objective to save setuptime cost and save the production time were successfully carried out. Three types of layout of production line was modelled and analysed. The first and second layout was a semi-automated production line where loading and unloading into machines and buffers were done manually and the third type of layout was fully automated layout where the robot performs the loading and unloading job. Two sorting criteria were defined in exit point of the buffer first one was based on similar job and second criteria was based on same route. Much of the production time and setup cost was saved effectively by utilizing these production elements. The draw backs of these kinds of models is it will be very expensive and may consume more space when used for large size jobs like in automobile firms, aircrafts parts, ship and rail carts hence these kinds of models can be used only when the jobs are small to medium in sizes, where storage cost and space required is less. Similar criteria can be applied to different conveyor model and its influence in production line to save cost and time can be studied in future.

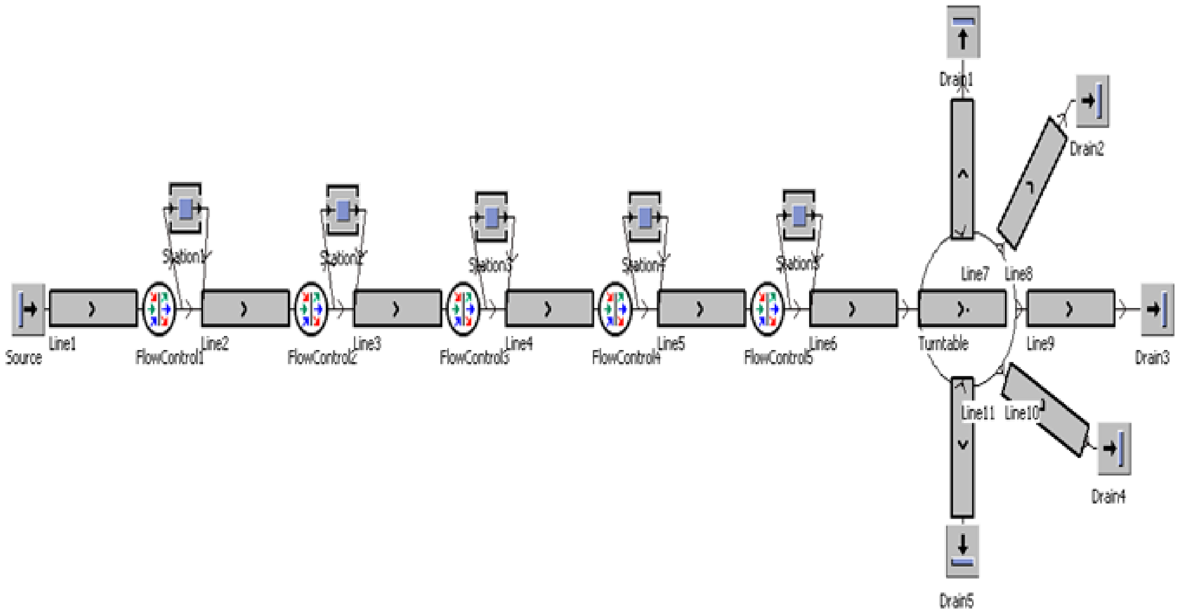

Fig 1: Layout 1

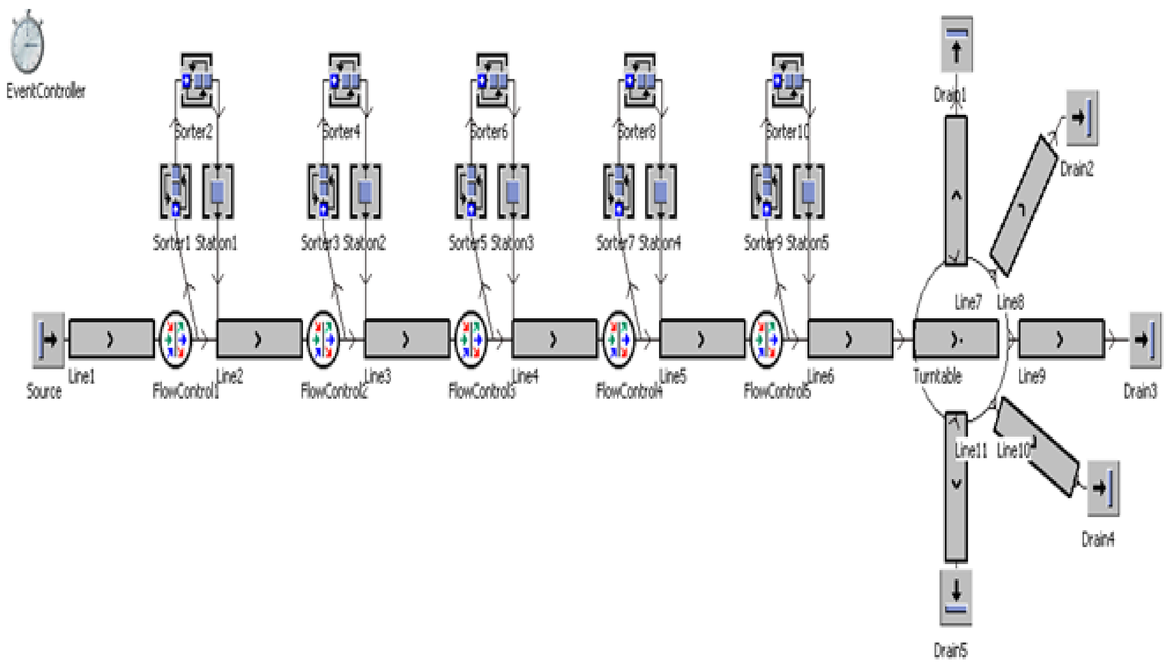

Fig 2: Layout 2

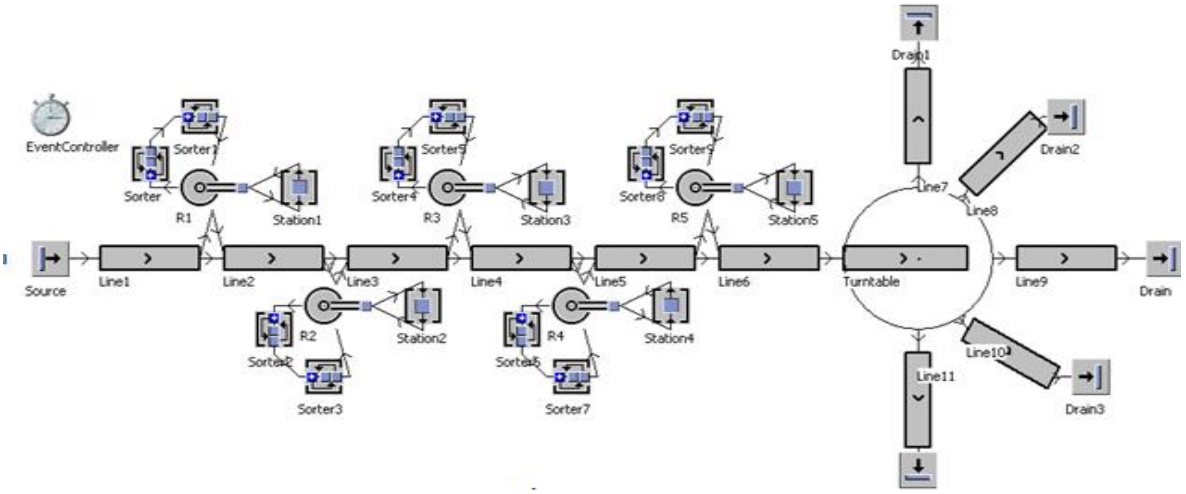

Fig 3: Layout 3

Table1. Processing Route information of each Job

Jobs	Route
Job1	Station1- Station3- Station5
Job2	Station2- Station3
Job3	Station1- Station3
Job4	Station2- Station3- Station4-Station5
Job5	Station1- Station4
Job6	Station2- Station4- Station5
Job7	Station1- Station5
Job8	Station2- Station4
Job9	Station1
Job10	Station3- Station5

Table2. Setup time and Operation time taken for each Job

Station	Operation Time (min)	Setup Time (min)
Station-1	**30**	**10**
Station-2	**15**	**7.5**
Station-3	**35**	**17.5**
Station-4	**25**	**12.5**
Station-5	**10**	**5**

Table 3 Details of sequencing in the buffer for station 1

Parts from source				Parts Entering Buffer 1			Parts Leaving Buffer 1			Parts Leaving Buffer 2		
Job6	Job1	Job4	Job10	Job1	Job1	Job3	Job1	Job1	Job3	Job1	Job1	Job1
Job8	Job1	Job6	Job6	Job1	Job3	Job9	Job1	Job3	Job9	Job1	Job3	Job3
Job3	Job1	Job3	Job8	Job7	Job3	Job7	Job7	Job3	Job7	Job3	Job3	Job3
Job9	Job8	Job6	Job7	Job7	Job9	Job9	Job7	Job9	Job9	Job3	Job3	Job7
Job4	Job3	Job7	Job10	Job9	Job7	Job3	Job9	Job7	Job3	Job7	Job7	Job7
Job6	Job7	Job9	Job9	Job3	Job7	Job9	Job3	Job7	Job9	Job7	Job7	Job9
Job9	Job7	Job3	Job10	Job5	Job5	Job9	Job9	Job1	Job9	Job9	Job9	Job9
Job4	Job3	Job4	Job7	Job1	Job9	Job3	Job3	Job3	Job9	Job9	Job9	Job9
Job6	Job9	Job5	Job6	Job5	Job3	Job9	Job7	Job5	Job5	Job9	Job5	Job5
Job5	Job8	Job6	Job8	Job7			Job5			Job5		
Job4	Job9	Job1	Job9									
Job3	Job5	Job3	Job9									
Job2	Job8	Job8	Job7									

Table 4 Total Simulation Time of a Production Line

Layout Model	Total Simulation Time
Layout1(Production Line without Buffer)	3days:04Hours:15Minutes:05second
Layout2 (Production Line with Buffer)	2days:19hours:43minutes:26seconds
Layout3 (Production Line with Buffer & Pick and Place Robot)	2days:08hours:56minutes

Table 5 Total Simulation time with the increase in the capacity of racks

Total simulation time for 10 racks	**2days:08hours:56minutes**
Total simulation time for 20 racks	2days:08hours:55minutes:25Second
Total simulation time for 30 racks	2days:08hours:55minutes:9Second

Table 6 Lower bound & Upper Bound of Sigma for processing Stations

Station	Range	Lower Bound (min)	Upper Bound (min)
Station 1	20	10	30
Station 2	7.5	7.5	15
Station 3	17.5	17.5	35
Station 4	12.5	12.5	25
Station 5	5	5	10

Table 7 Lower bound & Upper Bound of Sigma for Setup Time at Stations

Station	Range	Lower Bound (min)	Upper Bound (min)
Station 1	10	5	15
Station 2	3.75	3.75	7.5
Station 3	8.75	8.75	17.5
Station 4	3.75	3.75	7.5
Station 5	2.5	2.5	5

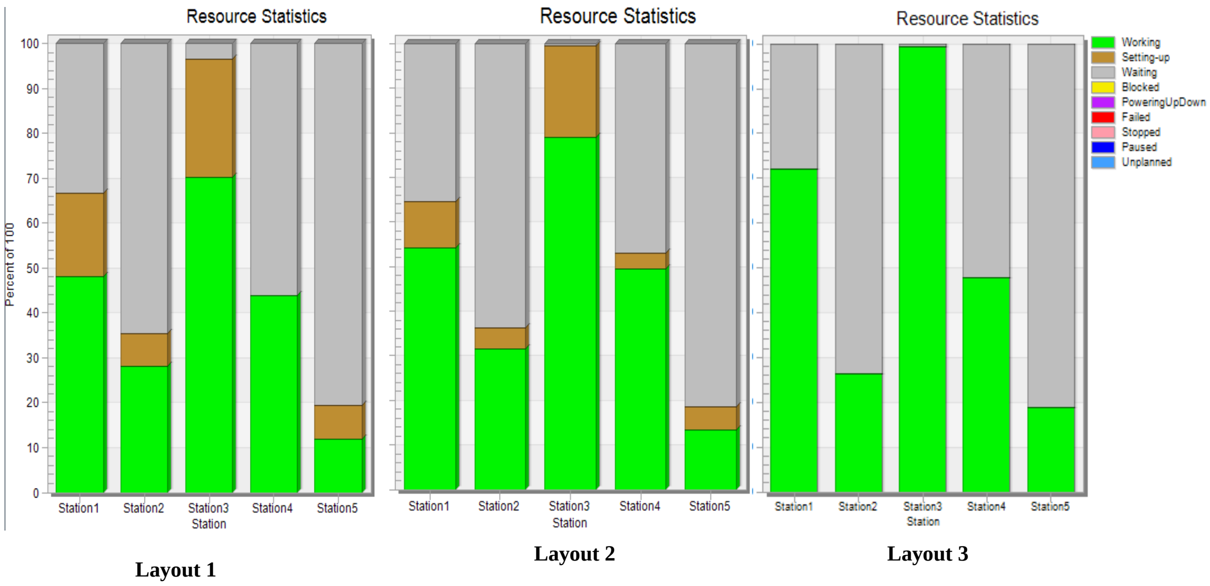

Fig 4: Percentage of Utilization of Machine for different Layouts

ACKNOWLEDGMENT

The authors convey their sincere thankfulness to the referees and the editor for their constructive comments, which have immensely helped to bring this paper to the present form.

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