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Job Sequence Optimisation Using Combinatorial Evolutionary Approach in High Variety/Low Volume Manufacturing Environment

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Abstract— Today's manufacturing industry is been through unprecedented degree of change in terms of high variety and low volume, high value, global competition, shortened product life cycles, change is management strategies, increasing quality requirements and customer expectations and increased process complexity. As a result, in recent years organisations have adopted towards optimisation of the manufacturing operations in order to stay in competition, sustain their operational performance and maximise their economic benefits. This paper exemplifies a novel approach for development of combinatorial optimisation framework using evolutionary algorithms and Discrete Event Simulation modelling to determine the optimal job sequence by taking in account multiple organisational constraints. Simulation model used in this research represents the working area at Perkins Engines Limited. This may enable organisations to deal with such a highly diversified product portfolio without jeopardizing the benefits of an efficient flow-production. In the proposed methodology, two objectives used are manufacturing lead time and total inventory holding cost to measure the effectiveness of proposed solution. However, chosen objectives can be changed according to the organisational priorities.

Index Terms — Combinatorial Optimisation, Job Sequencing, Lean Manufacturing, Process Improvement, Simulation Modelling, Process Synchronisation, Genetic Algorithms.

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1 INTRODUCTION

IN early twentieth century, craft production system failed to cope with dramatically increased customer demand of cars. As, skilled workforce was spending longer times to produce a single vehicle, which decreased the throughput and increased the production cost. These pitfalls of the craft manufacturing system inspired two major industrial revolutions. The first manufacturing revolution; the mass production system, developed by Henry Ford and his famous Model-T, which changed the requirements of production systems have changed dramatically by shifting manufacturing paradigms towards a cost efficient mass production of a single standardized product. Nowadays, a multitude customisable product options is selectable by the customers, so that the manufacturers of these products need to handle a (theoretical) product variety which exceeds several billions of models. For instance, a base model of a car can be modified according to customer requirements such as manual or electric sunroof, air conditioning, power window etc. [1]. By providing the high product variety organisations have put themselves ahead of their competitors, at the same time, however, it has augmented the manufacturing problems at production planning and scheduling level. As of this, manufacturing organisations in a wide range of industries nowadays are facing the challenge of providing a high product variety at a very low cost. This typically requires the implementation of cost efficient, flexible production systems such that various models of a common base product can be manufactured in intermixed sequences. However, it can have adverse effect in terms of extended lead times and increased waste (in terms of excessive inventory, transportation, overproduction, waiting and excessive motion), all of which adds to increased cost and lead times and decreased profits. According to [2], therefore, exploiting the sequence planning benefits is essential to stay competitive in high variety/Low Volume (HV/LV) manufacturing environment by maintaining the low manufacturing cost. There are numerous entities/processes involved within the manufacturing environment and most of these entities exhibit dynamic, unpredictable and complicated relationships among them, which makes it even more difficult for decision makers to choose over available job sequences. This poses a great challenge for the organisations not only how to respond proactively towards constantly changing business environment but also how to draw competitive advantage from the chosen methods. The use of intelligent techniques in the manufacturing field has been growing the last decades due to the fact that most manufacturing optimisation problems are combinatorial and most of these are NP Complete, i.e., there is no polynomial-time algorithm that can possibly solve them.

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2 SCOPE OF THE PAPER

This research has erected on Lean philosophy, which is derived from the second manufacturing revolution i.e. Toyota Production System (TPS), by taking the concept of continuous improvement. The main focus remains on targeting different manufacturing problems by considering the interdependencies exist between different WorkCentre and effect of improvement on overall organisational performance. The main emphasis of this paper remains on the job sequence optimisation problem, where the different organisational constraints been used such as product mix, variable setup, processing times, product routings and machine failures. Along this, paper highlights the effectiveness of evolutionary combinatorial optimisation method with simulation modelling for problem solving in a complex environment. The two optimisation objectives used are Manufacturing Lead Time (MLT) and Total Inventory Holding Cost (TIHC) to measure the effectiveness of proposed solution. Along this, proposed approach combines the genetic algorithms (GA) based combinatorial optimisation with discrete event simulation (DES) in order to increase the adaptability of proposed framework in wider range of problems, where user can;

1. Change the simulation model according to the change in manufacturing environment.
2. Represent the different/new scenarios.
3. Change the evolutionary objective functions according to the organisational objectives.
4. Access the Pareto optimal set of solutions in order to choose the other solution, which may be presents better trade-off than optimal solution w.r.to organisational objectives.

In current research, simulation model represents the working area at Perkins Engines Limited and this model been linked with the optimisation module in order to determine the optimal job sequence according to the selected performance measures. However, proposed approach is adoptable to different manufacturing and service environments as long as the problem can be represented using the simulation model.

3 Job Sequencing

Similar to other manufacturing problems (such as buffer size, job shop layout, scheduling, etc.), job sequencing problem is one of the essential problems that needs to be addressed to improve organisational performance by reducing the number of changeovers due to product mix. In fact, reduced changeovers may improve the MLT and TIHC. According to [3] the sequence in which jobs have been processed determines the performance of organisation, as one sequence may increase the MLT over other due to variable cycle time and setups associated with different part types. At the same time, job sequence can increase the inventory levels/cost as well due to the increased number of changeovers. Similarly [4] exemplifies the job sequencing problem as the ordering of different parts on a machine/s, such that the optimal sequence can be obtained for some measure of effectiveness according to selected performance measures. Each job is subjected to some of the organisational constraints such as setup and processing times, machine failure, start date, due dates, and product routings. All these constrains makes job sequencing as a NP complete problem, where all of the constraints needs to be satisfied up to certain extent by considering the knock-off effect on the preceding and succeeding WorkCentre.

According to [5] and [6], job sequencing is one of the most difficult combinatorial optimisation problems, as a large number of sequences exist in vast search space with objective function values may exist near to each other. This may increase the possibility of a large number of local optima. In addition, optimal sequence may not provide noticeable improvements when combined with the organisational constraints.

Similarly, the other aspect of job sequencing can be seen as due date assignments, by getting the optimal MLTs, which define the total manufacturing time required to complete the customer order. For instance, according to [7], knowing the total time required to fulfil customer order can provide more reliable due dates. Due dates can be either set externally by customer or internally by scheduling software/production planner, where the internally set due dates reflect the constraints imposed due to the variable setup times and processing times, product mix, routings and machine failures. Therefore, from the HV/LV manufacturing and current research perspective, the main focus of job sequencing remains to decrease the effect of variability due to the setup times and product mix, which may also assist in the due date assignments and scheduling.

4 Proposed Approach

4.1 Problem Statement

The job-shop scheduling problem consists of ordering n jobs $\{J_1, J_2, \dots \dots, J_n\}$ to be processed on m machines$\{M_1, M_2, \dots \dots, M_m\}$.

Each job $J_i$needs to be processed on machine M_k according the predefined routings, where $1 \leq i \leq n$ and $1 \leq j \leq m$ i.e. each job involves a number of different machining operations.

According to [8], there are potentially $(n!)^m$job sequences, although some of these sequences may be infeasible due to various organisational constraints. Some of the key considerations for problem statement are;

1. Each job contains the associated job number and quantity of parts to be produced.
2. Identical routings are defined with respect to each job, two or more jobs can follow same route.
3. Each machine can process only one job at a time according to the defined routings.
4. Any job can be processed at most one machine at a time.
5. Availability of a job to particular WorkCentre depends on the processing capacity and availability of preceding WorkCentre.
6. Once an operation is started it continued until it is completed.
7. Transportation time between the WorkCentre are zero.
8. Processing and Setup time are known in advanced and depends on the job type and triangular distribution is used to represent the processing and setup times in order to represent model close to reality.
9. Effect of operators is not considered in the proposed approach.
10. Each WorkCentre has dedicated buffer space to accommodate the effect of variability.

In this paper, a job sequence problem been investigated to improve the material flow through setup reductions as a part of process improvement by reducing the effect of variability in HV/LV manufacturing environment with respect to selected performance measures. Current research has focused on combinatorial optimisation using evolutionary algorithms combined with simulation modelling. For instance, two objectives have been considered, which are same as the organisational performance measures i.e. MLT and TIHC. In fact, the main aim here is to find all the possible trade-off among the multiple objective functions i.e. finding all the Pareto optimal solutions. Pareto optimal solution can be defines on the basis of domination rule. Researches have exemplified the concept of Pareto optimality based on two domination rules. These can be described as [9] [10];

A solution "S_1" is said to be dominate the solution "S_2"if and only if;

1. The solution "S_1" is no worse than "S_2" in all objectives and,
2. The solution "S_1" is strictly better than the solution "S_2" in at least one of the objectives.

According to the results from the combinatorial optimisation, therefore, one can define a job sequence J_i as an optimal sequence from a given set of Pareto optimal sequences $\{J_1, J_2, \dots \dots, J_n\}$ if and only if at least on objective (MLT or/and THIC) for J_i is strictly better than the entire set of Pareto optimal sequence.

The proposed approach can be seen as decision making tool while choosing a solution from the Pareto optimal set of solutions. Therefore, Pareto-optimal set contains the solutions from each generation and decision maker can chose optimal solution based on the organisational priorities and other management factors.

4.2 Genetic Algorithms as an Optimisation Model

The use of intelligent techniques in the manufacturing field has been growing the last decades due to the fact that most manufacturing are complex and optimisation problems are combinatorial. According to [11], there are a large number of combinatorial problems associated with manufacturing optimisation and most of them are NP complete, i.e. there is no polynomial-time algorithm that can possibly solve them, unless it is proved that NP. Therefore, heuristic methods are normally employed for the solution of these problems. Most of researchers have adopted the use of meta-heuristic techniques for large combinatorial problems to be able to search large regions of the solution's space without being trapped in local optima [12] and [13].

Research here has opted GA based combinatorial optimisation combined with DES tool as an iterative method to solve the job sequencing problem. The main aim here is to find all the possible trade-off's among the selected objectives i.e. MLT and TIHC by considering the organisational constraints and relation between succeeding and preceding WorkCentre. The main credit of using GA goes to their simpler implementation, applicability and adaptability in wider range of real world problems for different industrial sectors. For instance, [14] has applied GA based multi-objective optimisation to determine the optimal buffer sizes in HV/LV manufacturing environment according to the given organisational objectives to achieve the synchronous flow by reducing the level of variability, where the simulation modelling is used to represent the manufacturing environment. Researcher here has applied GA aligned with the drum-buffer-rope methodology to solve the bottleneck problem by determining the appropriate buffer locations and size. Similarly, [15] has applied genetic algorithms (GA) based optimisation for job sequencing problem in just-in-time (JIT) mixed-model assembly lines to reduce the variation of production rates and number of setups simultaneously due to diversified customer demand. Also, [16] has used a multi-objective GA for planning order release dates for a two-level assembly line to minimise the holding cost and backlogging cost by using the system constraints as known demand and due dates for finished product. In the scheduling framework, [17] have applied GA in production scheduling problem to achieve a better trade-off between on-time deliveries, shorter MLT's and maximum resource utilisation, where resources and buffer sizes are considered as constraints. There are other examples, where GA has been applied in wide range of applications, such as Optimisation (job shop scheduling, buffer size), Machine Learning (weather forecasting and prediction of protein structure), Automatic Programming (computer programs evolve for specific task or for other computational structure), Economic Models (development of bidding strategies and emergence of economic markets), Immune System Modelling, Ecological Modelling, Population Genetics Models, Interactions between Evolution and Learning and Social System Models [18],[19] and [14].

4.3 *Proposed Approach*

Proposed combinatorial optimisation approach has used GA to develop the optimisation engine, which is developed in C++ and been integrated with the Simul8 (DES tool). Simulation tool here represents the manufacturing environment and the different level of variability, such as routings, setup time, product mix, processing time and machine failures. Proposed optimisation model can be given as;

1. Create an initial random set of population "P" having "m" job sequences from the set of jobs, where "m" represents the population size, which can be given as;
$$P_i = \{p_{i1}, p_{i2}, \dots \dots, p_{i(m-1)}, p_{im}\}, Where\ 1 \le i \le n$$
and "n" represents the number of generations.
2. Score the initial set of job sequences "P_1" against the fitness function "F", which is derived from the other two fitness functions i.e. MLT and TIHC by using weighted sum approach and weights are generated randomly for each chromosome in order to maintain the randomness in population.
3. Loop for reproduction;
    1. Copy "k" best solutions to the next generation, as proposed method has used ***Elitism*** strategy to retain the best solution form each generation. Number of elite solutions is derived from the number of objectives involved in optimisation process i.e. in the proposed solution k **= 2**. In order to keep the dominated

solution for each objective.
2. Mating to combine solutions in the population according to selection probability based on their ranking in the population using multipoint crossover operator. Initial crossover probability is kept as 60%, but for the later generations it's calculated dynamically as solution converges.
3. Uniform multipoint mutation is used based on a random number "***r***" for each selected individual to introduce the solution variability. The uniform mutation here preserves the relation between the part number and associated quantity.
4. Along the mutation, inversion operator is used to induce the randomness in the population and to increase the probability to find the optimal solution quicker.
5. Copy "***m-k***" individuals to the next generation.
6. Check the termination criteria, if reached go out of loop else continue.

In the proposed approach, crossover and mutation probabilities are derived as population converges in order to maintain diversity. For instance, mutation probability goes high if population is stagnant for two consecutive generations. However, it needs to be within a limit in order to maintain a proper balance between exploration and exploitation ability of optimisation search optimiser algorithm.

4.4 Problem Representation

To represent the stated problem in ***section 4.1***, simulation model has been established using discrete model simulation tool (Simul8), which is been integrated with the optimisation algorithm. It is important to note that; used simulation model represents the working area at Perkins Engines Limited. Simulation model details are given by [14], as the model has been used to solve the bottleneck problem using evolutionary approach. The main attributes of simulation model are;

1. Generic names been used to represent the simulation model, for instance "***M1***, ***M2***, ***M3***, ***M4*** and ***M5***" represents the WorkCentre and each WorkCentre has a dedicated buffer space.
2. Triangular distribution has been used for work entry point to match system closely to real manufacturing environment. Also, inter arrival time has not been changed for different batch sizes.
3. Travelling time between workstations is kept as zero. Job loading is derived according to the sequence generated using genetic algorithm, there is no explicit dispatching rule is applied.
    a. Each work type has properties associated with it such as route to follow and processing time and setup time at different WorkCentre.

5 Results Discussion

Following parameters been used to collect the results;

1. Three batch sizes were used to collect data under different experiments; i.e. batch size 1, 5 and 10 and buffer size is used as 20 for all buffers.
2. 500 parts needs to be produced in total with 10 different work types.
3. Data is been collected using both with machine failure and without machine failure.
4. Genetic parameters;
   Population size = 20,
   Number of generations = 100,
   Simulation time = 20000 min,
   No of elite solutions = 2 and
   Crossover, mutation rates are calculated dynamically as solution emerges.
5. The set of final solutions represents the two dominant solutions based on each objective function i.e. MLT and TIHC (as described in Table 1). Decision maker, therefore can chose the solution based on the organisational priorities. For instance, completion of order may be higher priority than the cost involved for a prestigious client. On the other hand, to save cost due dates can be negotiated.

It is important to note that, ***Table 1***, only represents the optimal solutions w.r.to the MLT and THIC from Pareto optimal set for different batch sizes. There are other optimal solutions as well in the Pareto optimal set, which can be chosen as well if one of those solutions serve the organisational objectives better.

From ***Table*** 1, Job sequence optimisation has improved MLT significantly, as the focus remains on the minimising the changeovers to improve the flow of material. There is reduction in TIHC too, which is only coming from the reduced changeovers, as reduced changeovers contribute towards the queening time and queue size. Similarly, it is evident from the other performance measures that the level material flow is more streamlined when the number of setup's are decreased, which can be seen in the decreased ***%changeover*** for the WorkCentre "***M2***" and increased ***%working*** (***Table 2***). According to [14], in the given simulation model WorkCentre ***M2*** is a bottleneck and making any improvement should consider the knock-on effect on the other WorkCentre and modelling elements. The proposed combinatorial optimisation algorithm, therefore take in account the trade-off between M***LT*** and ***TIHC***, which are effected through the other performance measures as given in ***Table 2***. In other words, proposed combinatorial optimisation algorithm improves the selected performance measures without creating another bottleneck or affecting the system performance negatively.

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TABLE 1
MLT AND TIHC BEFORE AND AFTER OPTIMISATION

Experiment No.	Batch Size	Machine Failure	Dominant Solution	Before Optimisation MLT	Before Optimisation TIHC	Job Sequence Optimisation MLT	Job Sequence Optimisation TIHC	Optimal Job Sequence
1	1	Yes	LT	8897	103614	8008	94093	2:50 8:50 10:20 7:80 5:60 6:50 9:60 3:30 1:60 4:40
2			TIHC			8278	91280	1:60 6:50 7:80 8:50 5:60 3:30 9:60 2:50 10:20 4:40
3		No	LT	7297	84062	6835	82437	7:80 8:50 2:50 10:20 9:60 4:40 6:50 1:60 5:60 3:30
4			TIHC			7127	76694	5:60 7:80 10:20 9:60 3:30 2:50 6:50 8:50 1:60 4:40
5	5	Yes	LT	10016	108911	8001	93896	10:20 7:80 8:50 2:50 9:60 4:40 5:60 3:30 1:60 6:50
6			TIHC			8339	89856	9:60 5:60 6:50 1:60 8:50 2:50 10:20 3:30 7:80 4:40
7		No	LT	8653	93016	6834	79594	2:50 7:80 10:20 8:50 9:60 3:30 1:60 5:60 4:40 6:50
8			TIHC			6906	75506	2:50 10:20 3:30 8:50 7:80 9:60 1:60 5:60 6:50 4:40
9	10	Yes	LT	11559	112978	8007	88480	8:50 7:80 2:50 10:20 5:60 1:60 6:50 9:60 4:40 3:30
10			TIHC			8479	86457	7:80 2:50 3:30 8:50 10:20 9:60 1:60 6:50 5:60 4:40
11		No	LT	10348	98754	6834	74177	2:50 8:50 7:80 10:20 1:60 5:60 3:30 9:60 4:40 6:50
12			TIHC			6971	71048	7:80 10:20 3:30 8:50 2:50 5:60 1:60 9:60 6:50 4:40

TABLE 2
SELECTED PERFORMANCE MEASURES BEFORE AND AFTER OPTIMISATION

Work Centre	Performance Measure	With Machine Failures: Before Optimisation	With Machine Failures: After Optimisation	Without Machine Failure: Before Optimisation	Without Machine Failure: After Optimisation
M 1	Waiting %	38.38	33.97	44.03	37.8
	Working %	19.55	21.72	23.84	25.45
	Blocked %	27.23	29.49	32.11	36.65
	Stopped %	14.82	14.8	0	0
	Change Over %	0	0	0	0
M2	Waiting %	1.43	0.2	1.74	0.14
	Working %	71.25	79.16	86.88	92.75
	Blocked %	0	0	0	0
	Stopped %	14.6	14.57	0	0
	Change Over %	12.69	6.05	11.37	7.09
M3	Waiting %	58.64	57.14	73.56	72.43
	Working %	20.22	22.47	24.66	26.33
	Blocked %	0	0	0	0
	Stopped %	19.22	19.32	0	0
	Change Over %	1.89	1.04	1.76	1.22
M4	Waiting %	66.7	65.12	81.36	80.1
	Working %	14.83	16.48	18.08	19.31
	Blocked %	0	0	0	0
	Stopped %	18.01	17.88	0	0
	Change Over %	0.44	0.49	0.54	0.58
M5	Waiting %	65.08	64.41	75.88	75.42
	Working %	16.85	18.73	20.55	21.94
	Blocked %	0	0	0	0
	Stopped %	14.73	14.61	0	0
	Change Over %	3.31	2.24	3.56	2.63

Note: It is important to note that the data included in this paper is only for the 500 jobs. However, data is collected for the different number of jobs, for instance 1000 and 2000. Proposed approach has shown the similar trend for the other experiments.

3 Conclusion

Maintaining the performance of HV/LV manufacturing environment is one of the most challenging tasks, as high level of process/product variability and can increase the MLT and TIHC significantly. At the same time, this variability cannot be ignored, as most of it is derived from the customer demand. The research here exemplifies a novel approach for job sequencing system based on combinatorial optimisation and DES modelling that may help problem solver and decision-makers to accomplish the synchronous flow by reducing effect of variability. There is other HV/LV manufacturing issues have been addressed, which are;

1. Ability to adjust the mutation and cross-over rates in order to maintain the proper balance between exploration and exploitation ability.
2. Determining the optimal job sequence by considering the trade-off between LT and TIHC.
3. Ability to manage different level of variability by considering the effect of improvement of one performance measure on other.

In summary, the positive results have exemplified the effectiveness and robustness of proposed algorithm under highly unstable circumstances. Also, current research is carried out under a collaborative project, funded by the Technology Strategy Board and the proposed approach been validated by the industrial collaborators (TATA Steel and Perkins Engines Limited).

Along this, practical applications stem not only from the manufacturing industry, but also from many segments of HV/LV consumer goods industries can be applied, e.g. consumer electronics, food industry, clothing etc. as an improvement opportunity, the behaviour of algorithm can be improved by combining the optimisation process simultaneously with buffer size and batch size optimisation. Along this, other levels of variability can be considered such as the travelling time between the WorkCentre.

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