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Optimization of Multi-item Operation Sequences and Batch Size for Non-Parallel Capacitated Machines: A Case Study

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Abstract

Current work presents a case study that simultaneously addresses the classical problem of job sequencing and batch sizing in a manufacturing firm. The firm produces engines and transmission sets for automotive industries and is characterized by multi-stage processing of several sub-products followed by the final assembly. The firm processes 11 components using 23 machines to cater customer demand of transmission sets under constraints like machine capacity and delivery schedule. To propose an improvised schedule and batch sizes, a planning model is developed which also aims to improvise specific performance measurement criteria i.e. makespan. The problem is complex due to exceedingly large solution space, which precludes the use of any exact algorithm. A simulation based Genetic Algorithm (GA) approach is thus used to solve this optimization problem. Authors report successful implementation of the approach and demonstrate improvised results over the existing approach of the firm. The work assists operations manager for efficient planning, and constitutes a practical application of simulation-based optimization involving effective monitoring and control of production.

Keywords: Production Scheduling; Multi Machine; Batch Sizing; Simulation; Genetic Algorithm

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1. Introduction:

Production can be considered as one of those prime facets of industrial operations, which contributes towards maximum transformation and value addition in the product. Production planning has thus continued to be an area of interest for researchers. A few of the parameters that influence an efficient production plan are job sequence and production batch size. While sequencing directly affects the performance indicators like average number of jobs in the system, average job lateness, average completion time etc., lot sizing straight away impacts inventory, the number of setups and eventually production economics. The optimal decision related to these two parameters thus becomes pivotal for overall performance of the organization.

In the context of scheduling, significant efforts are being made by researchers and consequentially numerous algorithms are developed to address various scheduling problems and their extensions. The various scenarios in which scheduling was considered ranged from a single machine to multi machines, parallel machines to alternative machines and unrelated machines and so on [3,16,21]. Specific to multi machine, [17] considered six machines and proposed heuristics for scheduling. Likewise, [10] considered a maximum of ten machines for reducing makespan, but for a hypothetical scenario.

Besides, scheduling under different production environments such as flexible job shop and hybrid flow shop, FMS etc was also considered [4,6,27]. Eventually, it was realized that optimizing the production schedule by considering only one criterion is not sufficient as organizations aim to improve the multiple performance indicators simultaneously. This led to the development of multi criteria scheduling [12]. Considering this, integrated approaches also started gaining attention of researchers wherein the integration of production with maintenance and inspection policy was studied [1,8,19,25].

Specific to batch size planning, various meta-heuristics were proposed to be used under specific environments for solving

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lot sizing problem. For example, [18] considered a time varying approach to arrive at optimizing lot sizing decision so as to have lowest production cost. Algorithm considering item deterioration, demand pattern etc. were also developed [13]. It was also emphasized that lot size does affect production scheduling. And to leverage this correlation, joint optimization of scheduling and production batch size gained attention.

In this direction, efforts made by [11], addresses the simultaneous optimization with an aim to minimize the sum of weighted earliness, tardiness penalties, and setup costs. For a single machine, the work describes solving algorithms and imposes upper and lower bound to batch size for arriving at an optimized result. However such restriction on batch size may confine the feasible solution space and scope of finding a better solution is narrowed down. Similarly, for parallel machines, work by [26] has treated lot sizing and scheduling and proposed a "fix-and optimize" algorithm in which decision related machine loading is first fixed and rest of the decision are obtained using a solver. [20] also developed a model for scheduling and lot sizing which enables users to find optimal production quantity, sub-lot size, inventory levels etc. The model is tested for different scenarios using a hypothetical numerical example but has considered a few of the assumptions such as same process routes for all the products, negligible set up time, no precedence constraint etc. Further, the model considers only single day planning horizon and does not allow any backlogging. It can be observed that such observations lead to a significant deviation from the actual shop floor environment which, in reality, is much more complex.

It is evident from literature mentioned above and more, that various algorithms which suggest a solution for multiple versions of the scheduling and lot sizing problem are well acknowledged. But it also highlights that majority of the reported work considers multiples assumptions which are rarely observed on real shop floors. For example, in the case of slightest of commonality leading to a number of components getting processed on the same machine, all the jobs are considered to have same characteristics related to cycle time, setup time etc. Such an extent of similarity is rarely observed and is overly restrictive. Such assumptions lead to a simplistic replication of shop floor and thus significantly deviate from a real and complex manufacturing environment. It is also observed that the algorithms so developed are special-purpose algorithms i.e. each algorithm is developed for a specific environment to solve a particular problem. For instance, some algorithms are only applicable to single machines, some for two-machine problems while others for multiple parallel/related machines. Further, the effectiveness of such algorithms in handling the extension of the addressed problems is acutely discussed [7].
During exhaustive literature review, authors didn't come across a real industrial application of scheduling and lot sizing problem, which is applied to an environment that has more than 10 machines. Furthermore, such exact algorithms involve lengthy and complex equation, which requires thorough understanding of advanced mathematics and thus making it difficult for practitioners to interpret and apply [22]. Thus, practitioners prefer algorithms that are simpler, even though they may generate suboptimal solutions [9].

Current works attempt to overcome such limitations by developing a generic planning model which is flexible to accommodate variations of the manufacturing environment. It also aims to defy the above-mentioned assumptions made for arriving at optimal decision for job scheduling and lot sizing. It undertakes a case study of manufacturing enterprise; AVTEC Private Limited and demonstrates the improvised results

2. Industry Background, Description of Industrial Environment & Problem Summary

2.1 Industry Background

The current study is based on observations and findings derived from one of the manufacturing plants of a firm named AVTEC Pvt. Limited (CK Birla Group). The plant is located in Pithampur, India and manufactures power trains and precision engineered products for diverse applications in automotive and off highway industries.

2.2 Description of Industrial Environment

In its current form, the layout of the plant is broadly divided into multiple sections which are similar in terms of key manufacturing operations, kind of machines, process management etc. Therefore, instead of considering entire plant, a representative section is considered for the current study. This representative section manufactures "Transmission Sets" and caters to the demand of multiple customers by producing multiple variants of transmission sets. Functionality wise, all such variants are same but minor changes occur in few of the dimensions and material of constituent components. Even the manufacturing process for individual components doesn't call for any extra setup from variant to variants and thus for all the practical purposes, these variants can be treated same. In addition, the plant also caters to the demand of spares of these individual components. The demand of spares is different for different components, which creates unevenness in the total quantity of individual components to be produced.

In order to meet customer demand, at its maximum capacity, the section under consideration can run for 3 shifts a day and 6 days per week. Considering appropriate allowances for Personal, Fatigue, and Delay (PFD allowances), the maximum available time per day for production is 1162 minutes. However, depending on factors like demand, machine breakdowns, absenteeism, availability of raw material etc., the number of production days in a month may vary.

"Transmission Sets" produced are independent block comprising of sub-assemblies, intermediate assemblies, sub-components, parts etc. Most of these parts are bought out elements that are outsourced from multiple suppliers. The firm only focuses on the production of 11 critical and precision-engineered components, which eventually goes into final assembly of transmission. In absence of any one of these components, final assembly of transmission set cannot be completed and customer demand cannot be fulfilled. Thus a set of all these 11 in-house produced components is collectively called as "Whole Set". The raw material for these "Whole Sets" undergoes a wide range of machining operations including shaving, milling, shaping, machining, etc. which are carried out on multiple machines. The process flow for each of these components is predefined by the process engineers. However, the sequence in which these components are loaded on various machines can significantly affect production economies. A randomly planned production sequence may lead to either machine waiting for the component that is getting processed on another machine or component waiting for the machine which is busy processing another part. Considering complex process flow and production of multiple components on multiple machines, an optimized sequence of production holds prime importance for timely completion of "Whole Set" and fulfilling customer demand.

Likewise, production economies also get severely impacted by the decision related to production batch size. For example, a larger batch size of production of a component will hinder the timely production of remaining component. On the other hand, splitting the batch size into too smaller quantities will call for frequent set ups changes and will lead to decrease in available time for manufacturing. This highlights the need for optimized production batch size for different components. Such optimized batch size may be different for different operations on different components and may bring a non- uniformity in quantity produced of different components. To streamline this, organization assembles the maximum number of whole sets, which can be completed with the available quantity of various components produced. The remaining quantity of all the processed components is carried forward and deducted from the demand of individual component for next time period.

While optimizing production sequence and batch size, the organization faces various constraints such maximum available production hour, minimum lot size, precedence and succedence of individual operations, etc.

2.3 Problem Summary

The above mentioned description can be summarized as an environment of multiple non-parallel capacitated machines processing various components, each essential for the final product and having an individual and unique process flow. Currently, the decision related to the sequence of operations on individual machines and production batch size for each component on each machine is intuitive and influenced by production planner's limited domain knowledge. Such a person dependent planning approach may not be efficient and can negatively affect organization's performance. To develop a planning process where a person is independent and efficient, a data driven model based on the systematic algorithm is essential. Since the nature of the business is dynamic, it is expected that in future there may be change in the process flow, number of machines, number of components etc. It is therefore required that the model be generic and flexible enough to accommodate such variations. In addition, the model should also assist the managers in improving values for specific performance indicators such as makespan.

3. Notations: (In order of appearance in text)

$\lambda_{\mathrm{m_{is}}}$	Sequence Factor
β_{ij}	Production batch size for j^{th} operation on i^{th} component
π_t	Makespan for demand in period t
τ_m	Time at which m^{th} machine completes processing of all the jobs
M	Total Number of Machines
C	Total number of components required for "Whole Set"
J	Number of operations in the component with maximum number of operations
L	Number of component which goes through the machine with maximum number of processes
ω_{ij}	Wait time for j^{th} operation on i^{th} component

δ_{ij}	Set up time for j^{th} operation on i^{th} component
η_{ij}	Cycle Time for j^{th} operation on i^{th} component
S_t	Scheduled delivery time in period t
Q_i	Total finished Quantity of i^{th} Component
D_t	Demand quantity in period t
$\bar{a}_m$	Maximum available production time on m^{th} machine
d	Number of production days in period t
C	Number of components required for assembly of a transmission set
J_C	Number of Operations in process flow chart for c^{th} component
$\psi_{C_iO_{(j+1)}}$	Time at which j^{th} operation of i^{th} component is started
$\kappa_{C_iO_j}$	Time at which j^{th} operation of i^{th} component is completed
$\theta_{C_iM_n}$	Machine allocation Factor for i^{th} component on n^{th} machine
$\Phi_{M_nC_i}$	Scheduled production factor for n^{th} machine and i^{th} component
d	Number of production days in period t
$\alpha_{C_iO_j}$	Run length for j^{th} operation on i^{th} component

4. Assumptions, Model Development and Validation

4.1 Assumptions

Current research has following assumptions:

- Raw material for all components is available when needed for production.
- All machines can process only one component at a time.
- Operations are non-preemptive, i.e. once started, an operation cannot be disrupted until its completion
- All machines are continuously available.
- Production rate of individual machines are constant
- Each component is loaded only once to a particular machine

4.2 Model Development

As mentioned above, the organization's prime focus is to fulfill the customer demand of transmission sets in minimum possible time and thus organization's aim is to minimize the makespan of "Whole Sets".
The makespan will vary with the sequence in which individual components are loaded on different machines and the production batch size. These two decisions can be expressed as:

I. $Decision\ of\ Sequencing : \lambda_{\mathrm{m_{is}}}$, such that $\lambda_{\mathrm{m_{is}}} = \begin{cases} 1, & when\ \ i^{th}\ component\ is\ scheduled\ on\ m^{th} Machine\ \ in\ s^{th}\ \ production\ run \\ 0, & otherwise \end{cases}$

II. $Decision\ of\ Batch\ Sizing :\ \beta_{ij}$, such that
$\beta_{ij} = The\ Batch\ size\ for\ j^{th} Operation\ on\ i^{th} Component$, for all i and j, i ϵ [1,C], j ϵ [1,J] ∀ N

And objective of minimizing makespan can be mathematically mentioned as:

$Objective$:

$$Minimize\ (\pi_t) = \ Minimize\ \{\mathrm{Max}\ (\ \tau_m)\}\ , \forall\ m,\ \ m\ \epsilon\ [1, M], \tag{1}$$

Where,

$$\tau_m = \ \sum_{i=1}^{i=C}\sum_{j=1}^{j=J}\sum_{s=1}^{s=L}\{\lambda_{\mathrm{m_{is}}} \times [\omega_{ij} + \ \delta_{ij} + \ \ (\eta_{ij}\ \times \beta_{ij})]\} \tag{2}$$

$Subject\ to$:

- Dispatch Schedule Constraint:

The organization follows a policy of periodical dispatches, which are generally scheduled on weekly basis. This sets up a time constraint, which can be written as:

$$\pi_t \leq S_t \tag{3}$$

- Demand Constraint:

Besides the constraint of timely shipment, there is another constraint for the quantity of "Whole sets" to be shipped in a particular time period. This translates into constraint for minimum quantity to be produced, in order to fulfil the complete demand. The same can be written as:

$$\{Min.(Q_i)\} \geq D_t \ , \forall\, i, i \in [1,C] \tag{4}$$

- Maximum Available Production Hour per Machine Constraint:

Considering the Personal, Fatigue and Delay allowance, maximum available time per machine for production is 1162 minutes. Mathematically, same can be expressed as:

$$\bar{a}_m \leq 1162 \times d, \ \forall \ m, m \in [1,M] \tag{5}$$

- Precedent and Succeeding Operation Constraint:

Each component undergoes a series of operations before it gets completed for final assembly. The sequence in which these operations should be carried out is predefined in the "Process Flow Chart (PFC)" which is a structured document representing the sequential flow of activities. PFC clearly communicates the preceding and succeeding set of activities for all the operations and is arrived at by considering multiple parameters such as the feasibility of operation, change in the material property after each operation, dimensional tolerance etc. Deviation from process flow may lead to the devastating effect on quality of final product. This renders the constraint of preceding and succeeding operation, which can be written as:

$$\psi_{C_iO_{(j+1)}} \geq \kappa_{C_iO_j}, \forall \text{ i,j}, \ \text{i} \in [1,C], J \in [1,J] \tag{6}$$

- Component Multi-Allocation Constraint:

To ensure that at any point of time, a component is not allocated simultaneously on multiple machines for production, a machine allocation factor($\theta_{C_iM_n}$) is introduced such that:

$$\sum_{n=1}^{n=M}(\theta_{C_iM_n}) \leq 1 \ , \ \forall\, i, i \in [1, C] \tag{7}$$

Where,

$$(\theta_{C_iM_n}) = \begin{cases} 1, & if \ i^{th} \ component \ is \ processed \ on \ n^{th} Machine \\ 0, & otherwise \end{cases} \qquad for \ all \ t \in T \tag{8}$$

- Machine parallel production Constraint:

Likewise, to ensure that at any point of time, a machine is not processing multiple parts simultaneously, a "Scheduled Production factor "$\Phi_{M_nC_i}$" such that:

$$\sum_{i=1}^{i=C}(\Phi_{M_nC_i}) \leq 1, \tag{9}$$

Where,

$$(\Phi_{M_nC_i}) = \begin{cases} 1, & when \ n^{th} Machine \ is \ processing \ \ i^{th} \ component \\ 0, & otherwise \end{cases} \tag{10}$$

- Minimum Batch Run Length Constraint:

To avoid frequent machine set ups, it is required that for any particular batch should run for a minimum of one production shift i.e.

$$\{ \ Min.\, \alpha_{C_iO_j} \geq \left(\frac{1162}{3}\right) minutes \tag{11}$$

4.3 Modal Validation

In order to check the correctness of the model, simulation runs for some intuitive scenarios were performed. These scenarios were generated by altering the number of machines, number of component in whole set, time period etc. The results obtained were in line with the expected outcomes. For example, when the model was optimized for of 2 machines and 10 components in a simplified environment such as no job priorities, all jobs starting at first work centre etc., the results were aligned with conventional Johnson's rule. In addition, using the real shop floor data, the model is also critically examined and validated by process owners at AVTEC private limited.

5. Problem Complexity, Solution Approach, Data Set & Results

5.1 Problem Complexity

Conventional production scheduling problem of "M Job-1 Machine" can have M! feasible solutions. In the current work, considering the distributed process flow of components, it is safe to assume that each of the 23 machines, on an average, processes 6 components. This leads to the total number of feasible solution for production sequence to be as high as $(6!)^{23}$. In addition, for every single production run on the individual machine, there may be a variation in lot size that further increases the solution space by manifolds. Since the production manager needs to timely arrive at these decisions to start production, time to arrive at a solution also plays a critical role. Such a complex scenario, therefore, calls for carefully selected solution approach so that the results can be implemented on the shop floor at earliest.

Pseudo Code

```
Input: Population size 'e', crossover rate 'f', mutation rate 'g',
Output: Minimum Makepsan (π_t)
// Formulation
setParameters();
Define mean as the statistic for the simulation results;
defineDecisionVariables();
defineConstraints();
// Simulation based optimization
// Initilization
    Generate_random () e individuals;
    Save them in the population Population ;
//Evaluation and Rank based selection
    Compute_fitness (u) ∀ u ϵ e;
    Select the best solutions in Population and save them in New Population
for T=1 to termination do
//Crossover
    for j=1 to n do
        Select two individual u_a and u_b from Population based on top ranks
        Generate u_c and u_d ; by uniform crossover on u_a and u_b under rate f;
        Save u_c and u_d to Set
    end for
//Mutation
    for j=1 to n do
        Select one off S spring from Set;
        Apply non-uniform mutation rate g; // Generate new decision variables S'
    End for
    Determine sample of uncertain parameters using probability distribution functions;
    Recalculate the model using new sampled values and new decision variables;
    Calculate and store the new value of Makespan;
    if      S' is unfeasible then
        Update S 'with feasible solution by repairing S'
        endif
        update S with S' in Set
    Endif
Endfor
// Resulting minimum Makespan
Retun the best solution for π_t in Population;
```

5.2 Solution Approach

Problems like scheduling N jobs on a single machine, makespan minimization for parallel machines and economic lot size scheduling problem are known to be NP-hard Problem [14]. Since the current work considers a scenario which is the extension of those mentioned above, the same has been also considered as NP-hard. It is therefore unlikely to obtain the optimal solution for the current problem through polynomial-time-bounded algorithms. Alternatively, meta-heuristics techniques such as tabu search, simulated annealing etc. can be applied. One such stochastic search algorithm called Genetic Algorithm (GA) is applied for the current problem as its ability for performance and computational intensity has been demonstrated by various researchers [2,5,15]. "@ RISK" optimizer [24], which uses Monte Carlo simulation based GA approach, is used for the same in this research. The pseudo code for the same is as mentioned below and the GA parameters are as mentioned in Table 1.

Table 1. GA Parameters

Population Size	200
Number of Generations	100
Crossover Rate	0.1
Mutation Rate	0.5
Selection Scheme	Roulette wheel with elitist selection

5.3 Data Set

The generalized model is applied to real shop floor using the below mentioned Data set. Table 2 lists all 11 components that the firm produces to meet the collective requirement of whole sets and its spares. These components, based on their process flow, are routed through different machines. The list of all the machines is as mentioned in Table 3. The process flow of a representative component is mentioned in Table 4, which shows the sequence of operations, respective machines on which particular operation will be performed and corresponding cycle time and set up time as determined by Maynard's Operations Sequencing Technique (MOST).

Table 2. List of Components Processed in house for Whole set

S. NO	**Raw part Number**	**Finished Part Number**	**Description**	**Short Name**
1	BP7208Z02	BP7208Z	MAIN SHAFT	MS
2	BP7209Z/0-50	BP7209Z	CLUSTER GEAR SHAFT	CGS
3	BP7207Z02	BP0766Z	TOP GEAR SHAFT;	TGS
4	BP7212Z/10	BP0773Z	GEAR ASSY; 2ND MAIN	G2M
5	BP7213Z/10	BP0774Z	GEAR ASSY; 3RD MAIN	G3M
6	BP7214Z/10	BP0775Z	GEAR ASSY 5TH MAIN W/SYNCHRO	G5M
7	BP7211Z/10	BP0772Z	GEAR ASSY LOW MAIN	GLM
8	BP7204Z/0-20	BP7204Z	GEAR;5TH,COUNTER	G5C
9	BP7205Z/12	BP7205Z	GEAR;COUNTER REVERSE	GRC
10	BP7206Z/10	BP0771Z	GEAR ASSY.;REVERSE IDLE,5 SPEED	GRI
11	BP7203Z/12	BP7203Z	GEAR;REVERSE,MAIN SHAFT	GRM

Table 3. Machine Description

Machine No.	**Description / Operations**	**Machine No.**	**Description / Operations**
1	Deburring & Chamfering	13	Shaping
2	Helical Shaping	14	Hobbing
3	Gear shaving	15	Deburring and Chamfering
4	Shaving-1	16	Shaving -2
5	Gear tooth chamfering	17	Shaving -3
6	Turning -1	18	Gear Hobbing-3

7	Turning -2	19	Key way milling
8	Spline Rolling	20	Drilling
9	Soft Grinding	21	Spline Rolling-1
10	Gear Hobbing-1	22	Spline Rolling-2
11	Shaft Hobbing	23	Grooving and Turning
12	Gear Hobbing-2		

Table 4. Representative Process Flow Chart (PFC) with Cycle Time and Setup Time

Main Shaft (MS)					
S. N.	**Op. No.**	**Process Description**	**Machine**	**Set-up time (Minutes)**	**Cycle time (Minutes)**
1	30	Turning operation- Set Up 1	Turning -1	30	3.6
2	40	Turning operation-Set Up 2	Turning -2	30	4
3	50	Soft Grinding operation for Section A1	Soft Grinding Machine	30	1.3
4	60	Soft Grinding operation for Section A2	Soft Grinding Machine	30	1.6
5	70	Spline Hobbing Operation	Hobbing Machine	90	2.23
6	80	Spline Rolling of Section A1	Spline Rolling Machine	15	0.56
7	90	Oil Hole Drilling Operation	Drilling Machine	45	1.3
8	100	Keyway Milling Operation	Milling Machine	45	1.86
9	120	Spline rolling Section D	Spline Rolling Machine	90	2.66

These PFCs are executed on the shop floor after collating the demand quantity of Transmission sets and demand quantity of spares of individual components. This demand quantity from customers regulates the dispatch and is represented in Table 5 below.

Table 5. Dispatch Commitment

Sr No	Product	Dispatch Commitment		
		Sept'15	Oct '15 (Tentative)	Nov'15 (Tentative)
1	Engines (Var.1)	500	700	700
2	**Transmission for Customer 1**	**500**	**700**	**700**
3	**Transmission for Customer 2**	**2500**	**2500**	**2500**
4	Engines (Var.2)	350	300	300
5	Engines (Var.3)	48	TBD	TBD
6	AVTEC -Engines	10	20	20

5.4 Results

The model was optimized with the above-mentioned data set, to arrive at an improved value for batch size and production sequence. Table 6 shows a part of the log of total time elapsed vis-à-vis progressive improvement in objective function (Goal Results). The complete log is represented in Figure 1, which demonstrates that the marginal improvement is diminishing as the time progresses. To trade-off between the quality of result and time elapsed, a termination condition is being imposed to end the optimization. It will stop when either of the below mentioned conditions is fulfilled:

1. Best individual value doesn't improve over 200 generations
2. Total improvement of the last 10 best solutions is less than 0.1 percent

Such termination may not provide the global optimum and the solution can be improved further. However, the optimization results obtained here are within the confidence bound of 95 percent, which provides an outlook for the quality of the learned local optimum against the global optimum.

A close look at Table 6 illustrates that for the first production run on machine 1, the components GRC should be loaded for operation number 20 and the batch size should be 350. Likewise, G2M for operation number 40 and G5M for operation number 20 should be loaded on machine 2 and 3 respectively for their first production run and the respective batch size should be 450 and 550. These figures are highlighted in Table 7.

Table 6: Representative Log of Progress trial

Trial no.	Iterations	Goal Result (Mean)	Elapsed Time (Minute)
14583	100	91154	24.63
38947	100	71569	62.58
62847	100	42265	101.56
77589	100	23458	122.05
92568	100	22596	162.2
96586	100	21908	169.45

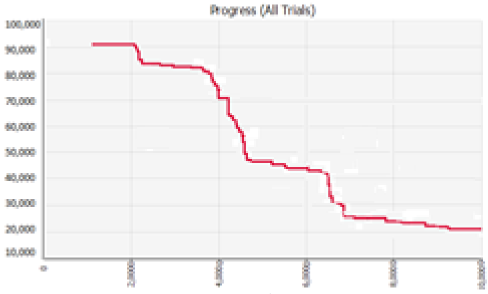

Figure 1. Log of All Trials

The final result is collated in the form of "Integrated Operations Schedule", a representative part of which is displayed in Table 7.

Table 7. Integrated Production Plan

PRODUCTION RUN	Machine 1		Machine 2		Machine 3	
1	Component	GRC	Component	G2M	Component	G5M
	Operation	20	Operation	40	Operation	20
	Batch Size	350	Batch Size	450	Batch Size	550
2	Component	GRM	Component	GRC	Component	GLM
	Operation	40	Operation	60	Operation	20
	Batch Size	450	Batch Size	450	Batch Size	550
3	Component	GRI	Component	TGS	Component	G5C
	Operation	40	Operation	80	Operation	30
	Batch Size	450	Batch Size	250	Batch Size	600

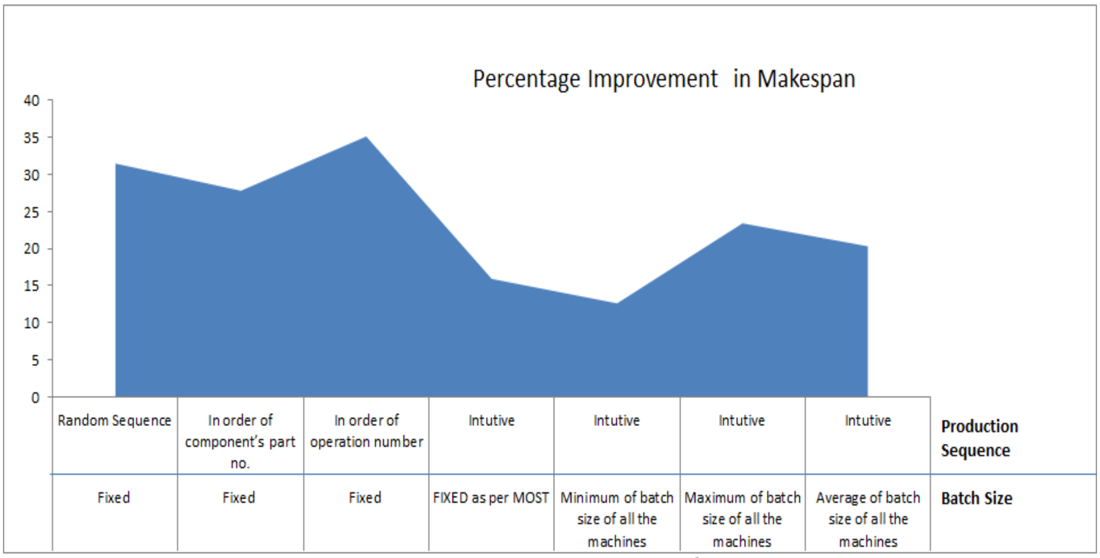

Figure 2: Percentage Improvement in makespan

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Considering the “Whole set” requirement and constraint of process flow chart, conventional priority rules for scheduling like First Come First Serve (FCFS), Shortest Processing Time (SPT), Longest Processing Time (LPT), etc. cannot be applied in the current scenario. However, the makespan arrived at by using proposed approach was compared against makespan of several other schedules, which were arrived at using different approaches. These approaches and corresponding makespan time is shown in Table 8 and summarized in Figure 2.

Table 8. Makespan for various approaches

PROPOSED APPROACH (GA based Simulation for joint optimization of production Schedule and Batch Size)		Makespan = 21108.35	
Conventional Approaches		Makespan for demand of September'15 (minutes)	Percentage Improvement using integrated approach
BATCH SIZE	PRODUCTION SEQUENCE		
FIXED as per MOST	Random Sequence	30810.54	31.48
FIXED as per MOST	In order of component's part no.	29255.59	27.8
FIXED as per MOST	In order of operation number	32548.63	35.14
FIXED as per MOST	Intuitive	25105.92	15.9
Minimum of batch size of all the machines	Intuitive	24158.35	12.6
Maximum of batch size of all the machines	Intuitive	27584.32	23.4
Average of batch size of all the machines	Intuitive	26485.36	20.30

Work by [23] indicates that a minimum makespan usually implies a high utilization of machines. The same has been reflected when the machine utilization of individual machine was compared before and after the application of proposed approach. The same is illustrated in Figure 3 below.

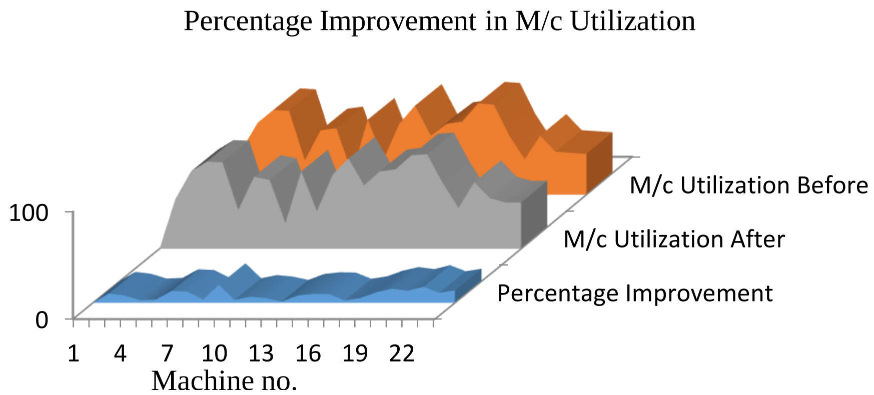

Figure 3. Improvement in machine utilization

It is evident that for all the machines, the utilization has increased and for some machines, the gain is as high as eleven percent. It can be thus stated that the schedule arrived by simulation based GA for joint optimization of scheduling and batch sizing has significantly outperformed the schedule arrived at by other approaches including the one that was previously applied by the organization.

6. Conclusion

Current work presents a case study performed at manufacturing firm. Using a simulation based GA approach, it simultaneously addresses the lot sizing and job sequencing problem which is solved by applying Genetic Algorithm. The model is first validated and later optimized to minimize the makespan time. The results of proposed approach are compared with conventional approaches and significant improvement was observed which demonstrates the superiority of proposed approach. Further, the current model is applicable to all the planning periods. Such flexibility of planning time frame, though complex to model, provides wider visibility and better control over industrial operations and also assists practicing managers for efficient decision making. Considering the improvement realized in performance indicator, proposed approach can be seen as the promising solution for next generation enterprise level performance optimization.

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Compliance with Ethical Standards

- Conflict of interest: The authors declare that they have no competing interests.
- Research involving human participants and/or animals: No such involvement in the current research work.
- Informed consent: Affiliated Institute was informed for their consent for this work.

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