Mixed Model Production Sequencing in an Automobile Industry: A Case Study

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Mixed Model Production (MMP) is a Just-In-Time (JIT) tool to achieve level production in multi-product environments. Products are sequenced to achieve organizational goals in MMP systems. Researchers consider Production Rates Variation (PRV) as a criterion to evaluate MMP sequences in JIT-centric systems. This paper analyses the existing production sequence in an automobile manufacturing industry in India. We use a heuristic approach to solve the production sequencing problem with the objective of minimizing PRV. The paper proposes a production sequence that has a small PRV value as compared to the existing sequence, which helps to achieve the JIT objectives.

1. Introduction

1.1 Mixed Model Production Systems

Mixed Model Production (MMP) or Mixed Model Assembly Line (MMAL) is the Just-In-Time (JIT) tool to achieve level production. It is the production of multiple kinds of products on a repetitive basis, in a mixed fashion and at a single line or station (Nicholas, 1998). Production becomes smoother when batch sizes are small and theoretically maximal smoothing is achieved by scheduling production at final assembly in batches of size one. In a multi-product environment it is necessary to develop a regular cycle among these items while ensuring a relatively smooth work load. MMP systems enable manufacturers meet demand for a variety of products in an efficient way. If the demand for each product is too low to use dedicated manufacturing lines or facilities, MMP is used to produce many similar but not identical products.

The major issues to be addressed in MMP systems are: (i) Designing and balancing the line and (ii) Sequencing the different product models. The Mixed model production sequencing is a problem of determining the sequence of introducing models to the mixed model assembly line. The sequencing has to be done considering the main organizational goals which are crucial to the efficient implementation of the Just-in-Time production system (Monden, 1983).

Objectives in MMP Sequencing Problem: Various objectives are considered in finding the optimal MMP sequences in literature. Boysen et al. (2009) categorized these objectives broadly into two classes. (i) Minimizing work overload (utility workers) and (ii) Just-in-Time objectives. The objective of JIT-centric sequencing approaches is to distribute the material requirements evenly over the planning horizon. This is to achieve the steady demand rate of materials over time (Joo et al., 1993) which is an important condition for JIT manufacturing. Different models are composed of different product options and thus require different materials, subassemblies and parts. So the model sequence affects the demands of these items over time. As an assembly line is commonly coupled with preceding production levels by means of a JIT-supply of required materials, the model sequence needs to facilitate this. Therefore a large number of researchers have approached the mixed model sequencing problem with this objective of keeping a constant usage rate of every part used by the line. The goal chasing algorithm also belongs to this category. The first mathematical model of the Toyota system is proposed by Miltenburg (1989), which defines two basic production systems: the multi-level and the single-level system. Miltenburg (1989) formulated the mixed model sequencing problem as a non-linear integer programming problem with the objective of minimizing the total deviation of actual production rates from the desired production rates. Miltenburg and Sinnamon (1989) analyzed a multi-level mixed model assembly line with four levels such as products, subassemblies components and raw materials. Leu et al. (1996) developed a genetic algorithm to solve a sequencing problem with this goal for a multi-stage production system. Sumichrast and Clayton (1996) evaluated the existing algorithms for a sequencing problem with this goal. Sumichrast et al. (1992) compared several procedures for sequencing problems with this goal by using simulation analysis and provided guidelines for selecting most efficient sequencing procedure for achieving their objectives.

Production Rates Variation: Miltenburg (1989) introduced an assumption in mixed model production systems that all products require the same number and mix of parts in the model. Under this assumption, minimizing the variation in production rates of the final product achieves minimizing the variation in all parts usage rates. Then the multi-level scheduling problem reduces to a single level problem. Kubiak (1993) distinguished the part level and product level problems based on this assumption and called the product level problems as product rates variation (PRV) problems. It is also called Miltenburg's usage metric (Mansouri, 2005). The original multi-level problem was also called as Output Rate Variation (ORV) problem. Many researchers have used PRV as the criteria to evaluate the MMP sequences (Mansouri, 2005, Kubiak & Sethi, 1991). The research efforts on PRV are summarized by Kubiak (1993) as well as by Dhamala and Kubiak (2005). The

product rate variation is calculated using equation 1 shown in section 2. This is a measure of deviation of actual production from the desired production and also a measure of production levelling.

Genetic Algorithm in MMP Sequencing Problem: The MMP sequencing is a NP-hard combinatorial optimization problem. Computational time is a critical factor in sequencing since it is a short term planning. Hence a number of researchers have used evolutionary algorithms and other heuristic procedures in solving the MMP sequencing problem. Genetic Algorithm (GA) is the mostly used evolutionary algorithm in the MMP sequence optimization problem. Genetic algorithms are search algorithms that mimic natural selection and natural genetics. They work by applying the survival of the fittest strategy on string structures with ordered yet randomized information exchange to form robust global optimizers. Since its introduction by Holland (1977) various versions of the algorithm have been developed and have been used in a wide variety of applications particularly in combinatorial optimization problems.

To implement GA, a coding is employed to represent the parameters in the problem to be searched. Then, the search procedure is started by forming a population of initial solutions. Then the GA operations selection, crossover and mutation are employed to improve the search repetitively as measured by a fitness function. The process continues until the termination condition is reached. In the case of MMP sequencing problem, each solution is just a sequence of the parameter values of the problem (chromosome), and the individual sites on the chromosome where parameter values are stored are called genes (Leu et al., 1996). Each chromosome represents a sequence of models to be produced in a cycle (e.g. ABABACAD or AAAABBCD) and each gene on the chromosome represents the individual model A,B,C or D. Once the number of units in a cycle is known, the initial population of random feasible initial solutions can be generated. Each initial solution is merely a different permutation of the feasible number of models. A fitness function is used to evaluate and select the better performing solutions which themselves become candidates for improvement using the genetic operations of crossover and mutation. The criterion to evaluate the sequences such as production rates variation (PRV) becomes the fitness function.

Although a number of genetic operators have been developed by different researchers (Starkweather, 1991) many of them need modification to satisfy the feasibility conditions of the sequencing in MMALs. The feasibility in the sequencing problem can be stated that the number of genes representing a model type should be equal to the number of units of that model type specified by MPS. The first research on the application of genetic algorithms MMP sequencing problem is carried out by Hyun et al. (1998). The objective was to solve single objective MMAL sequencing problems. They also proposed a method that can take advantage of the parallelism inherent in GAs to find diverse Pareto optimal solutions particularly for multiple objective sequencing problems in MMAL. The key to the method is a new evaluation and selection mechanism, called Pareto stratum-niche cubicle.

Ponnambalam et al. (2003) studied the performance of the selection mechanisms and showed that the genetic algorithm that uses the Pareto stratum-niche cubicle performs better than the genetic algorithm with the other selection mechanisms. They compared the Pareto stratum-niche cubicle and the selection based on scalar fitness function with respect to the objective of minimising variation in part-usage, minimising total utility work and minimising the setup cost. Kim et al. (1996) modified several existing binary operators to handle MMAL sequencing problem. They also developed a new binary operator called Immediate Successor Relation Crossover (ISRX). Mansouri (2005) proposed a Modified Genetic Algorithm (MOGA) which was able to find good solutions in terms of pareto-optimality. Three genetic operators namely crossover, inversion and mutation were used in the proposed MOGA. The major challenge in using GAs in MMP sequencing problem is to satisfy the feasibility condition during the genetic operations. The existing operators are to be modified or new operators are to be developed to maintain the feasibility of the new solutions.

Though the MMP sequencing problems are well researched, real world case studies reported are very few. Real sequencing problems involve a large number of product sets with high variance in demand. This case study analyses the existing production sequence in a leading automobile manufacturing industry in India. We use a heuristic approach to solve the production sequencing problem with the objective of minimizing PRV. The paper proposes a new production sequence which has a base and varying component. The resultant sequence has a small PRV value as compared to the existing sequence, which helps to achieve the JIT objectives.

2. The Problem Statement

This paper addresses the problem of optimizing MMP sequences with just-in-time objectives for an automobile manufacturing production line. The objective function considered is minimization of Production Rates Variation (PRV). Continual and stable part supply can be realized when the demand rate of parts is constant over time. This objective is significant to a successful operation of the system. Under the assumption that all products require the same number and mix of parts in the model, the variation in production rates of the final product achieves minimum in all parts usage rates. Thus, the objective can be achieved by matching demand with the actual production. In this paper, the following model is used which is found in Mansouri (2005). This quantity can be taken a measure of production levelling.

$$U = \sum_{k=1}^{D_T} \sum_{i=1}^{a} \left(x_{i,k} - k \frac{d_i}{D_T} \right)^2 \tag{1}$$

U = Production rates variation of a production sequence
a = Number of unique products to be produced

d_i = Demand for product i, i=1,2,...,a
D_T = Total number of units for all products
$x_{i,k}$ = Total number of units of product i produced over stages 1 to k, k = 1,2,...,D_T

3. Analysis of the Existing Production Situation

One of the production lines in a leading automobile industry in India is selected for the case study on mixed model production sequencing. The line manufactures commercial passenger cars in different varieties. We collected production details for one week and summarized the data to identify the different models and the production sequence. Description of the different models manufactured is summarized in Table 3.1. It is observed that 15 models are produced in the same line. The number of each model is determined from the forecasted demand and from any current orders. The 15 models are produced in a sequence that repeats after 3 days. Daily manufactured quantities of different models are given in Table 3.2.

Table 3.1 *Description of Different Models of Cars Manufactured*

Model No.	Model Name (Names are not real)	Colour	AC Make (Names are not real)	Market	Drive	Destination/ Language
1	NS	PLW	TUBROS	DOMESTIC	RHD	INDIA/ENGLISH
2	NS	JTS	TUBROS	DOMESTIC	RHD	INDIA/ENGLISH
3	NS ER6	PLW	TUBROS	DOMESTIC	RHD	INDIA/ENGLISH
4	NX	PLW	TUBROS	DOMESTIC	RHD	INDIA/ENGLISH
5	NX	JTS	TUBROS	DOMESTIC	RHD	INDIA/ENGLISH
6	NX ER6	PLW	TUBROS	DOMESTIC	RHD	INDIA/ENGLISH
7	NX ER6	JTS	TUBROS	DOMESTIC	RHD	INDIA/ENGLISH
8	TA NG3	JTS	BHR	EXPORT	RHD	NA/NA
9	TA NG3	BGR	BHR	EXPORT	RHD	NA/NA
10	CLG MISTA	CVG	BHR	EXPORT	LHD	NA/NA
11	CLG MISTA	JTS	BHR	EXPORT	LHD	NA/NA
12	HALZA LHD	SPR	BHR	EXPORT	LHD	NA/NA
13	HALZA LHD	JTS	BHR	EXPORT	LHD	NA/NA
14	YX CBS ER6	JTS	TUBROS	DOMESTIC	RHD	INDIA/ENGLISH
15	YX CBS ER6	PLW	TUBROS	DOMESTIC	RHD	INDIA/ENGLISH

Table 3.2 *Existing Manufacturing Schedule*

Model No.	Day 1 & Day 4	Day 2 & Day 5	Day 3 & Day 6
1	35	21	16
2	0	3	12
3	15	14	15
4	41	33	31
5	0	2	10
6	25	28	21
7	0	5	9
8	17	31	7
9	0	2	23
10	2	0	0
11	3	0	0
12	0	0	3
13	0	0	1
14	0	0	2
15	2	0	5
Total	**140**	**139**	**155**

Analysis of the Current Production Sequence: Two sequence parameters, the Production Rates Variation (PRV) and number of set-ups, are evaluated for the current production sequence. Table 3.3 shows that the PRV values for the sequence on all the days are much higher. The PRV is a measure of production levelling and a higher value indicates poor levelling of production. Since the set-up times are very small for the automated line, its value is less significant. The case study aims to propose a new production schedule which improves the PRV value and thus levelling the production process.

Table 3.3 *Existing Production Sequences*

Days	Production sequence	Number of set-ups	PRV
1 & 4	1 1 3 1 1 4 1 1 10 4 4 4 4 4 1 10 4 6 4 8 3 3 6 8 4 4 4 4 11 4 4 1 1 4 1 1 11 1 1 1 1 1 8 1 1 1 11 6 3 8 1 1 1 8 4 1 15 1 1 8 4 1 4 3 4 4 4 15 3 1 8 4 1 6 4 8 1 1 3 3 8 3 6 6 4 4 8 4 4 1 1 8 3 6 6 6 8 1 1 1 4 8 6 6 6 3 8 4 4 4 4 8 3 4 6 3 6 6 4 4 6 6 6 6 4 6 4 4 4 4 4 8 3 6 6 3 8 6 6 6	88	13409.44
2 & 5	8 1 1 1 1 8 4 1 1 4 8 4 1 1 6 4 8 1 4 4 4 8 4 1 4 4 8 6 4 4 1 8 1 4 1 6 8 4 4 3 3 8 3 6 6 1 8 1 3 4 3 8 4 6 4 3 8 4 6 3 3 8 6 3 1 8 6 3 2 6 8 1 1 4 6 8 1 4 8 7 4 8 6 4 8 4 1 8 2 4 8 4 4 8 6 4 8 1 3 8 6 6 8 4 6 8 4 3 8 7 7 8 7 6 8 4 7 8 2 6 6 6 8 6 3 6 5 5 4 4 6 6 6 6 6 9 3 6 9	114	10231.45
3 & 6	3 6 3 3 8 4 6 4 4 9 3 2 6 2 9 1 6 5 4 9 4 1 4 1 9 3 3 4 4 9 4 4 3 1 9 2 4 6 5 8 6 6 4 1 9 4 4 4 1 9 4 5 1 4 9 2 4 2 2 9 5 6 6 6 8 7 6 1 4 9 6 6 1 4 9 3 2 9 3 6 1 6 9 6 7 4 3 8 2 4 4 4 4 7 9 6 4 6 3 9 3 3 5 7 9 14 7 7 5 9 4 5 14 4 9 3 15 7 12 8 15 15 7 2 8 6 13 7 15 9 6 5 12 5 8 4 15 12 3 9 4 2 2 2 9 1 1 6 1 9 1 1 1 4 5	132	6088.74

From the weekly demand details, the average daily demand is calculated. This demand is used to determine a base production sequence which is to be repeated on all days. The genetic algorithm based approach is used to determine this base sequence with the objective of minimizing PRV value. Some models have to be produced in excess quantity over the base quantity. These are to be interspersed with the sequence. Table 3.4 shows the weekly demand details of individual models and calculation of base quantity (average demand). Table 3.5 shows the interspersion required for the models over the base quantity.

Table 3.4 *Weekly Demand Details and Calculation of Average Daily Demand*

Model No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Weekly Demand	144	30	88	210	24	148	28	110	50	4	6	6	2	4	14
Avg. Daily Demand (6 days per week)	24	5	14	35	4	24	4	18	8	0	1	1	0	0	2
Avg. Demand X 6	144	30	84	210	24	144	24	108	48	0	6	6	0	0	12
Balance Demand to be interspersed	0	0	4	0	0	4	4	2	2	4	0	0	2	4	2

Table 3.5 *Interspersion of Balance Demand over the Base Production Quantity*

Day\Model	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Day 1 & 4			1			1	1	1	1						
Day 2 & 5										1			1	1	1
Day 3 & 6			1			1	1			1				1	

4. Genetic Algorithm (GA) Based Approach for Sequencing

The MMP sequencing problem falls into the category of NP hard combinatorial optimization problems and thus a large sized problem may be computationally laborious to solve (Tsai, 1995). Computation time can be a critical factor in choosing a method of solving the sequencing problem since real time alteration of model sequences is often necessary when demand pattern changes or part shortage occurs (Hyun et al. 1998). Because of this, most of the researchers in this area use heuristic methods to solve MMP sequencing problem. This study uses a genetic algorithm based approach which consists of different stages as explained below.

Representation and Initialisation: In GA each chromosome represents a sequence of models to be produced in a cycle (e.g. ABABACAD or AAAABBCD) and each gene on the chromosome represents the individual model A,B,C or D. Once the number of units in a cycle is known, the initial population of random feasible initial solutions can be generated. Each initial solution is merely a different permutation of the feasible number of models. Initially a population of random sequences are generated and the population size is taken as 100.

Fitness Function: A fitness or evaluation function is used to evaluate and select the better performing solutions which themselves become candidates for improvement using the genetic operations. The specific form of evaluation function depends on the objective function being considered. The fitness of an individual solution dictates the number of copies of that solution in the mating pool. The more copies an individual receives, the greater is the probability that the characteristics will

be repeated in subsequent generations. Since the objective function considered in the present problem is a minimization problem, a transfer function is used to map this to a fitness function. The transfer function used in this paper is

$$F_i = T_{\max} - T_i$$

Where F_i is the fitness function of the chromosome i, T_i is the objective function value of a sequence i and T_{max} is the largest objective function value in the current generation.

Selection and Reproduction: The reproduction operator is used to select individuals from the current population to become parents of the next generation. Parents are selected according to their fitness value. Here, roulette wheel selection is used as the selection process. According to this method, the probability of selection of a particular sequence P_i is calculated as

$$P_i = \frac{F_i}{\sum F_i}$$

where F_i is the fitness value of the sequence i.

Genetic Operations: The selected chromosomes go to the mating pool for genetic operations to be done on it. Here three genetic operators, cross over, inversion and mutation are used. Randomly 60 percent of the sequences in the mating pool go for crossover and mutation operations, while 40 percent go for inversion and mutation operations.

Crossover: We used the modified order crossover (modOX) developed by Hyun et al. (1998). This crossover method preserves the feasibility of chromosomes after the operation. The elements from the mating pools are selected in pairs and they undergo crossover with a crossover probability 0.8. Two crossover points are randomly selected from both the parents. The elements between crossover points in one parent (P1) are copied into an offspring O1 in the same position as they appear in P1. Then the copied elements are randomly deleted from the other parent P2 and the remaining elements in P2 are copied into the undetermined positions in the offspring in the same order as they appear in P2. The second offspring is created by alternating the roles of the two parents. The modOX crossover would create offspring that would preserve the relative order in parents. An example is given in Figure 3.1.

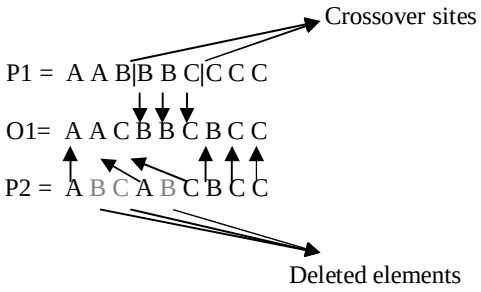

Figure 3.1 *modOX crossover*

Inversion: Individual chromosomes are selected from the mating pool to undergo inversion operation with an inversion probability 0.8. A single inversion site is generated randomly in the parent string. Then the offspring is formed by inverting the string about the inversion site. The elements after the inversion site in the parent string are copied to the offspring to start from the first position. Then the remaining positions are filled with the elements of the parent string coming before the inversion site in the same order. An example is given below.

O = B B A C A B C C

Mutation: After crossover or inversion operations, each string is selected for the mutation operation. A position in a string is selected for mutation with a mutation probability of 0.1. The element in the selected position of the string is randomly exchanged with another element in the same string. The mutation operation helps to extend the search into previously unexplored areas of solution space.

Replacement Strategy: When the genetic operations are completed for the present generation, the offspring are evaluated based on the objective function and compared with the existing solutions in the mating pool. Only those solutions which are well performing compared with the current solution is admitted to the new population. Thus the fittest among the two becomes the population for the next generation.

Termination of the Genetic Algorithm: In each generation, the best sequence is identified. The stopping criterion is implemented by means of a user defined number (UDN). When succeeding iterations which does not improve the solution reaches the UDN, the algorithm is terminated. Here we use a UDN value equal to 50. On termination, the program gives the best sequence, its objective function value and the CPU time.

5. Computational Experimentations

The genetic algorithm (GA) based approach for the MMP sequencing problem is coded in Scilab version 5.4.1 and run on a core i5 processor at 2.60 GHz with Windows 7 and 4 GB RAM. The program is validated by solving the example problems in Mansouri (2005) which resulted in getting the same optimal values. Here, the best sequence is based on the average daily demand and it forms the base sequence. Table 5.1 shows the base sequence, number of set-ups required and the PRV value. The balance quantity of the models over the average demand is to be interspersed within this base sequence. We propose to manufacture these items at the end of each day so that the level production schedule is least disturbed. The resulting sequences on all the days are shown in Table 5.2. It shows that the PRV value for this proposed sequence is much less than that of the existing sequence.

Table 5.1 *Best Base Sequence Generated by the Algorithm*

Base Sequence generated by the algorithm	No. of set-ups	PRV
1 3 4 6 1 4 9 8 3 6 6 4 8 4 1 4 2 9 8 5 6 1 4 3 4 8 6 1 7 3 4 6 1 8 2 4 9 4 1 4 6 8 5 7 6 1 6 4 3 8 4 11 4 1 1 6 8 4 9 3 8 1 4 12 3 6 1 6 4 15 8 4 6 4 1 2 4 1 6 6 4 3 9 3 7 8 1 8 4 1 4 4 1 6 3 5 1 9 8 4 6 6 4 8 15 4 1 7 3 4 6 1 8 2 4 9 3 6 4 6 8 3 1 1 4 3 4 6 4 8 6 1 4 2 9 8 5 6 1 4	134	305.46

Table 5.2 *Proposed Production Sequences*

Day	Sequence	No. of set-ups	PRV
1 & 4	[Base sequence]+ 3 6 7 8 9	139	451.10
2 & 5	[Base sequence]+10 13 14 15	138	609.22
3 & 6	[Base sequence]+ 3 6 7 10 14	139	542.98

6. Results

We studied the operations in a car production line of an automobile manufacturing industry for 1 week and summarized the details of different models (Tables 3.1 and 3.2). It is identified that 15 models of cars are manufactured in the line. The existing production sequence is analysed by finding its production rates variation (Table 3.3). The average daily demand is calculated from the weekly demand of individual models. This forms the base sequence that repeats every day. The proposed genetic algorithm based approach generates the best base sequence. The plant has to produce some models above this base quantity. For this, the excess quantities of these models are produced at the end of each day. This gives an almost level production sequence on all the days. The Production Rates Variation (PRV) for the proposed schedule is only 5% of that of the existing sequence. But the number of set-ups required has increased (Table 5.2).

7. Conclusions

A new production schedule is proposed for the automobile manufacturing line using a genetic algorithm based approach. The existing production sequence is not levelled because the production quantity varies on each day. The PRV value is also high. The proposed production sequence supports the manufacturing plant to achieve level production, which in turn helps to become a Just-In-Time organization. The reduced value for production rates variation supports this claim.

The number of set-ups has increased slightly for the new sequence which can become an issue if the set-up times are considerable. This study has considered a single parameter, production rates variation, as the objective of sequencing. In practical situations, the organizations may have to consider other parameters, where the proposed sequence may not be efficient. Hence further analysis of the system may identify more parameters that depend on the production sequence. The solution approach improves and becomes more realistic when these factors are considered in the objectives of the sequence optimization.

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