BALANCING AND SEQUENCING OF MIXED-MODEL U-LINES WITH MULTIPLE OBJECTIVES

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Abstract: This study deals with the mixed-model U-lines utilized in Just-In-Time (JIT) systems. A multi-objective simulated annealing algorithm for balancing and sequencing of mixed-model U-lines to simultaneously minimize absolute deviations of workloads across workstations, parts usage rate, and cost of setups is presented. Since the performance measures considered in the study are conflicting with each other the proposed algorithm suggests much flexibility to decision-makers.

1. Introduction

Mixed-model production is crucial to respond diversified expectations of today's costumer perspective. In such a production environment, more than one product with similar production characteristics or different models of a product are produced or assembled on the same line. Production lines on which mixed-model production is performed are called as the Mixed-Model Lines (MMLs). Balancing and sequencing of MMLs is important for an efficient use of these lines (Kim et al., 2000a). Mixed-Model Line Balancing (MMLB) is the problem of assigning tasks to sequential workstations by satisfying some constraints and optimizing some performance measures such as minimizing the number of workstations for a given cycle time, minimizing the cycle time for a given number of workstations, smoothing work overload, and maximizing the efficiency of MMLs. Mixed-Model Sequencing (MMS) is the problem of determining production sequence of models produced on the line by optimizing a performance measure. This performance measure can be one or more of the following goals: (i) smoothing the usage rate of parts used in the line, (ii) minimizing the total cost of setups, and (iii) minimizing the deviation of workloads across workstations.

The first of above goals is the most commonly considered criteria in the literature. This ensures that the usage rate of each part consumed by the final line is as uniform as possible (Aigbedo and Monden, 1997). The second goal is related to minimize the cost of setups which occur when adjusting operations from one type of models to another. JIT systems prefer such a production sequence that provides an intermixing of products and reduced cost of setups (McMullen and Frazier, 2000). The third goal is related to minimize the deviation of operation times required by each model in each cycle. This goal also provides a measure to maximize the operator efficiency and minimize the risk or cost of conveyor stoppages on the line (Xiaobo and Ohno, 2000).

The successful implementations of JIT principles offer a number of benefits to increase the effectiveness of the mixed-model production. U-lines on which mixed-model production is performed are called as Mixed-Model U-Lines (MMULs). As MMLs, a successful utilization of MMULs requires effective solutions to two important problems (Sparling and Miltenburg, 1998): (i) Mixed-Model U-Line Balancing (MMU/LB) and (ii) Mixed-Model U-Line Sequencing (MMU/MS). The U-Type shape of MMULs forces decision-makers to consider MMU/LB and MMU/MS dependently. This is mostly due to the utilization of crossover workstations in this type of line shape. Two different models may be worked in the same crossover workstation of a MMUL while only one model is worked in each workstation of a straight line (Miltenburg, 2002). By means of balancing and sequencing, this is the most important difference between two different line shapes. The types of two different models worked in a crossover workstation, thus the workload of this workstation may differ depending on the production sequence of MMUL. It can now easily be said that workloads of workstations may vary depending on both the line balance and the model sequence of the MMUL. The new problem dealing with the simultaneous consideration of MMU/LB and MMU/MS is called as the Mixed-Model U-Line Balancing and Sequencing (MMU/BS) problem (Kim et al., 2000b).

2. Literature Review

Sparling and Miltenburg (1998) first studied the MMU/LB and MMU/MS problems. They proposed an approximate solution algorithm. Their algorithm first transforms the MMU/LB into Single-Model U-Line Balancing (SULB) problem by calculating weighted average task processing times and merging each task's precedence diagrams into a combined precedence diagram. Then the problem is solved by a SULB algorithm to find an initial solution for MMU/LB problem. They also proposed a smoothing algorithm to reduce the model imbalance of the initial solution. The objective of this smoothing algorithm is to minimize the Absolute Deviation of Workloads (*ADW*) across workstations by solving MMU/LB and

MMU/MS problems sequentially. Kim et al. (2000b) proposed a co-evolutionary algorithm to solve MMU/BS problem simultaneously. The co-evolutionary algorithm proposed by Kim et al. (2000b) aims to minimize *ADW* for a given number of workstations and uses such a concept that the solution obtained from MMU/LB problem is input to MMU/MS. Miltenburg (2002) developed a genetic algorithm for solving MMU/BS problem simultaneously. The model of Miltenburg (2002) aims to minimize *ADW* and deviation of part production quantities in a JIT environment to facilitate "level" production.

To the best knowledge of the authors, there has been no study dealing with the multiple objective MMU/BS so far. This paper deals with the simultaneously balancing and sequencing of MMULs utilized in a JIT environment. A Simulated Annealing (SA) algorithm is proposed to solve MMU/BS problem with the objectives of minimizing usage rates, minimizing setup costs, and minimizing deviations of workloads across workstations.

3. Performance Measures

The performance measures considered in this study can be classified into two categories:

(i) *Balance and sequence dependent performance measure* (*ADW*):

This measure was used to evaluate the workload smoothness of *MMULs* by Sparling and Miltenburg (1998) and Kim et al. (2000b). *ADW* may vary depending on both the balance and the model sequence of *MMULs*. *ADW* can be computed as follows (Kim et al., 2000b):

$$ADW = \sum_{j=1}^{K}\sum_{r=1}^{L}\left|W_{jr} - C_{\min}\right| \tag{1}$$

Where;

K	number of workstations utilized on mixed-model U-line,
MPS	minimum part set,
L	total number of products for one *MPS* (or, length of the model sequence for one *MPS*),
W_{jr}	workload of workstation j at cycle r,
C_{min}	theoretical minimum cycle time,

(ii) *Sequence-dependent performance measures*:

Two different sequence-dependent performance measures are considered; cost of setups and parts usage rates. Most of researches that focussed on the sequencing of mixed-model lines assume that the cost of setups and parts usage rate of a workstation, are depended only the production sequence of the line. However, a workstation consists of several tasks. Although common tasks among different models exist a task's completion time can be equal to zero for some models in the sequence. If a task completion time is equal to zero for a model, this task is not performed for this model, thus no setup and no part usage is required. For instance, suppose the model sequence of a *MMUL* is ABCAC and the completion time of task i is equal to zero for model C. Hence, the model sequence of the *MMUL* for task i should be considered as ABA. In this study, the cost of setups and parts usage rates are calculated for each task and then the total costs of model sequences are considered as the sum of setups and sum of parts usage rates for each task.

The parts usage rate measure which was presented by Miltenburg (1989) is employed. This measure was also employed by McMullen (2001). The usage rates (U_i) and setup costs (S_i) of tasks can be calculated as follows:

$$U_i = \sum_{k=1}^{L_i}\sum_{m=1}^{P_i}\left(x_{km} - k \times \frac{d_{im}}{L_i}\right)^2 \tag{2}$$

$$S_i = \left(\sum_{k=2}^{L_i} s_{ik} \times c_{ik}\right) + c_{i0} \tag{3}$$

Where;

P_i	the number of different models which require task i,
d_{im}	demand for model m for one MPS_i,
L_i	total number of products for one MPS_i (or, length of the model sequence for one
s_{ik}	1, if the model at position k of MS_i is different from the model at position k-1 of MS_i; 0, otherwise,
c_{ik}	cost of setup that occurs when adjusting task i from the model at position k-1 of MS_i to the model at position k of MS_i,
c_{i0}	cost of setup to initialize a new MPS_i production,
x_{km}	total number of units of model m produced over stages 1 to k

4. Multi-Objective Simulated Annealing Approach

Simulated annealing (SA) is a metaheuristic which was introduced by Kirkpatrick et al. (1983) and has been a focus of interest for solving almost all kinds of combinatorial optimization problems. Solutions in a combinatorial problem are equivalent to states of a physical system, and the cost of a solution is equivalent to the energy of a state (Aarts and Korst, 1989). To escape from getting trapped into local minima, SA accepts not only better solutions but also worse solutions with a probability associated with the state of the system.

This paper proposes a simulated annealing approach for simultaneously balancing and sequencing of U-lines which have a finite number of workstations. The travel times of operators work on the U-line are assumed to be ignorable.

Cost function: The cost function of the proposed SA algorithm is the weighted sum of three performance measures:

$$\text{Minimize } E = w_{ADW} \times \frac{ADW}{ADW_0} + w_{TS} \times \frac{TS}{TS_0} + w_{TU} \times \frac{TU}{TU_0} \qquad (4)$$

Where;

TS: total setup cost of mixed-model U-line for one MPS production,

TU: total usage rate of mixed-model U-line for one MPS production,

ADW_0, TS_0, TU_0: initial values of performance measures,

w_{ADW}, w_{TS}, w_{TU}: weights associated with performance measures.

Initial solution: The initial line balance and initial model sequence for the proposed approach are generated randomly by satisfying all precedence constraints and *MPS* restrictions.

Neighbourhood generation: A neighbour solution can be either a new line balance or a new model sequence. A new line balance is generated by reallocating task among workstations while a new model sequence is generated by changing positions of models in model sequence. Initially, three random numbers (p_1, p_2, p_3) are specified to determine the type of new neighbour solution. A neighbour solution can be;

(i) a new line balance generated by *swapping* two randomly selected tasks with the probability of $p_1 \times p_2$,

(ii) a new line balance generated by *inserting* a randomly selected task into a different workstation with the probability of $p_1 \times (1-p_2)$,

(iii) a new model sequence generated by *swapping* two randomly selected models in model sequence with the probability of $(1-p_1) \times p_3$,

(iv) or a new model sequence generated by *inserting* a randomly selected model before to another randomly selected model with the probability of $(1-p_1) \times p_3$.

The neighbour solution generator logic given above allows us to consider line balancing and model sequencing problems of mixed-model U-lines simultaneously.

5. Conclusions

The MMULs are important elements of JIT systems. The problem of balancing and sequencing of MMULs is studied in this paper. The problem considered in this study is to find such a line balance and a model sequence to the MMULs that some performance measures are simultaneously optimized. The combinatorial nature of this problem makes it difficult to solve when the problem size increases and forces us to develop approximate algorithms to obtain optimal or near-optimal solutions to the problem. This study proposes a simulated annealing-based heuristic approach to MMU/BS. The proposed approach is capable of minimizing *ADW*, setup cost, and part usage rate of the MMULs while all of the constraints are satisfied. Results show that the proposed approach presents much flexibility to the decision-makers.

References

Aarts, E. and Korst, J., 1989, Simulated Annealing and Boltzman Machines. John Wiley and Sons, New York.

Aigbedo, H. and Monden, Y., 1997, A parametric procedure for multicriterion sequence scheduling for Just-In-Time mixed-model assembly lines. *International Journal of Production Research*, **35**, 2543-2564.

Kim, Y.K. and Kim, J.Y., 2000a, A coevolutionary algorithm for balancing and sequencing in mixed model assembly lines. *Applied Intelligence*, **13**, 247-258.

Kim, Y.K., Kim, S.J. and Kim, J.Y., 2000b, Balancing and sequencing mixed-model U-lines with a co-evolutionary algorithm. *Production Planning and Control*, **11**, 754-764.

Kirkpatrick, S., Gelatt, C.D. and Veechi, M.P., 1983, Optimization by simulated annealing. *Science*, **220**, 671-679.

Mcmullen, P.R. and Frazier, G.V., 2000, A simulated annealing approach to mixed-model sequencing with multiple objectives on a just-in-time line. *IIE Transactions*, **32**, 679-686.

Mcmullen, P.R., 2001, A kohonen self-organizing map approach to addressing a multiple objective, mixed-model JIT sequencing problem. *International Journal of Production Economics*, **72**, 59-71.

Mıltenburg, J., 1989, Level schedules for mixed-model assembly lines in just-in-time production systems. *Management Science*, **35**, 192-207.

Mıltenburg, J., 2002, Balancing and scheduling mixed-model U-shaped production lines. *International Journal of Flexible Manufacturing Systems*, **14**, 119-151.

Sparling, D. and Miltenburg, J., 1998, The mixed-model U-line balancing problem. *International Journal of Production Research*, **36**, 485-501.

Xiaobo, Z. and Ohno, K., 2000, Properties of a sequencing problem for a mixed model assembly line with conveyor stoppages. *International Journal of Operational Research*, **124**, 560-570.