Achieving Reliable Delivery in Supply Chains: The Control of Uncertainties
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Abstract
Time-based competition and market globalization make it imperative for supply chains to have reliable product deliveries within customer required lead times. This may not be easy to achieve in view that manufacturing activities are subject to various uncertainties. Furthermore, a delay of one manufacturer may propagate to others through precedence relationship. To improve delivery performance, it is critical to reduce the variance of product lead times. Motivated by the six sigma quality movement, a variance control technique is developed where lead time variances are accurately calculated and significantly reduced through effective scheduling individual manufacturers as well as coordinating across a chain with limited communication requirements. Numerical testing results demonstrate that the new approach is effective to schedule manufacturers on a supply chain to achieve on-time and reliable deliveries.

Keyword: Manufacturing scheduling, Supply chain coordination, Six sigma movement, Variance reduction, Lagrangian relaxation, and Stochastic dynamic programming.

1. INTRODUCTION
A supply chain contains multiple autonomous or semi-autonomous organizations such as suppliers, manufacturers, distributors through which products are manufactured and delivered to customers. Pressed by market globalization and time-based competition, a major concern in the supply chain management is to achieve reliable deliveries of final products within customer specified lead times. This, however, is not easy to achieve in view that manufacturing activities are subject to various uncertainties (e.g., uncertain material arrival times and uncertain operation processing times). In addition, manufacturers on a chain are increasingly relying on their suppliers to provide raw material or component parts, and delay of one manufacturer may propagate to others through precedence relationship. To improve overall product delivery performance, it becomes imperative to reduce variances of lead times by effectively scheduling individual manufacturers and coordinating across the chain. This, however, presents challenges since an appropriate solution methodology is lacking to estimate and reduce variances of product lead times through manufacturing scheduling. In view that manufacturers of a supply chain generally have their own private information and decision-making authority. Effective coordination should be developed without accessing others’ private information or intruding their decision-making authority.

After a brief literature review of Section 2, a decentralized supply chain model will be presented in Section 3. For simplicity, each manufacturer is abstracted as a job shop with key characteristics, such as uncertain material arrival times, uncertain operation processing times abstracted. Each manufacturer is to be scheduled with the goal to meet the requested order due dates. Motivated by the six sigma quality movement ([4] and [5]), an effective approach presented in Section 4 is developed to improve the delivery performance of individual manufacturers by adding penalty terms for variances of order lead times to their objective functions. A variance control technique is developed to calculate and reduce variances of order lead times by using stochastic dynamic programming without excessive computational requirements.

To improve overall delivery performance, a coordination technique is developed to synchronize activities of members across a chain with limited communication requirement. The key idea is to let scheduling of upstream manufacturers provides the predicted material arrival time distribution for downstream manufacturers; while downstream manufacturers provide upstream manufacturers the information about additional costs (i.e., tardiness costs) caused by the scheduling (order completion times) of upstream manufacturers. In this way, uncertainties and costs associated with individuals’ scheduling are effectively captured and propagated across the chain. Decision adjustments are made within individual members without accessing others’ private information and authority, and cross-organization cooperation is enhanced.

Numerical testing results are presented in Section 5. The effectiveness of the variance control technique to reduce variances of order lead times for a single shop is demonstrated by cases with different uncertainty levels. The effects of setting different penalty weight for variances of lead times on the performance of the new approach are also examined. The last example demonstrates the value of the coordination technique to obtain a good solution for a multi-shop problem by comparing its performance with that of a centralized coordination approach, where information sharing among all manufacturers can be achieved by converting the problem into a single job shop scheduling problem.

2. LITERATURE REVIEW
The Six Sigma methodology requires estimate and control of process variation to improve product quality ([4] and [5]). The approach has been used by Narahari et al. (2000, [8]) and
3. PROBLEM FORMULATION

3.1 Problem Description and Modeling Convention

Organizations in a supply chain may be divisions within one or different companies and located at various places. Since they are mostly autonomous or semi-autonomous with private information and individual decision making authority, centralized models and the corresponding methods are not suitable to coordinate their activities. A decentralized model will, therefore, be established with schematic presented in Figure 1, where individual manufacturers are denoted by $M$. Raw material has to go through a series of manufacturers before becoming the final products. Manufacturers are autonomous and cooperating decision makers linked through precedence relationship. For a particular manufacturer $M_i$, its orders may require material or component parts from its upstream manufacturer $M_{i-1}$ and may provide material for orders in its downstream manufacturer $M_{i+1}$. It can be seen that the product on-time delivery is affected by order delivery performance of all manufacturers, and this motivates developing a systematic way to reduce variance of order lead-times for individual manufacturers to achieve overall reliable on-time delivery.

For simplicity, an individual manufacturer will be modeled as a job shop and there are $F$ manufacturers in total. A particular manufacturer $f$ contains multiple machine types with the capacity of type $h$ machine at time $k$ given and denoted as $M_{kh}^f$. There are $I$ orders to be processed and each order is to go through manufacturer $1, 2 \ldots$ to $F$ in a sequential manner. The $i_{th}$ order ($i = 1, 2, \ldots$ to $I$) in manufacturer $f$ is denoted as $(f, i)$ and the subset of orders denoted as $O_f$. An order $(f, i)$ may require material or component parts from its upstream manufacturer $f-1$ and be associated with a given due date $d'_f$ specified by the customer. Order $(f, i)$ has to go through a series of $J_f$ operations, with the $j_{th}$ operation denoted as $(f, i, j)$ and the last operation denoted as $(f, i, J_f)$. The constraints and objective function for individual manufacturers are briefly presented below.

**Operation Processing Time Constraints.** Each operation needs to be scheduled on a machine of the required type for a random amount of time.

$$c_{jh} = b_{jh} + p_{jh} -1, \forall (f, i, j).$$

where $b_{jh}$ is the beginning time of operation $(f, i, j)$, and $c_{jh}$ the completion time; processing time $p_{jh}$ is a random variable with a given distribution, and it is assumed that the processing times for different operations are independent.

**Operation Precedence Constraints.** Operation $(f, i, j + 1)$ cannot be started until its preceding operation $(f, i, j)$ has been completed possibly plus a possible required slack-time time $s_{jh}$.

$$c_{jh} + s_{jh} + 1 \leq b_{j+1h}, \forall (f, i, j) \neq J_f.$$ (2)

These constraints can be extended to other cases, e.g., the first operation of order $(f, i)$ cannot be started until its requested material has arrived plus a possible required slack time:

$$a_{jh} + s_{jh} \leq b_{j1h}, \forall (f, i) \in O_f,$$ (3)

where $a_{jh}$ is the material arrival time for order $(f, i)$.

**Expected Machine Capacity Constraints.** It is required that the number of active operations scheduled on a particular machine type $h$ should be less than or equal to the capacity of that machine type at any time. Let $\delta_{jkh}$ be the operation indicator and defined to be one if the operation $(f, i, j)$ is active at time $k$ on machine type $h$ and $\delta_{jkh} = 0$ otherwise, the machine capacity constraints are formulated as following:

$$\sum_j \delta_{jkh} \leq M_{kh}^f, \forall k, h.$$ (4)

The above constraints couple decision variables belonging to different orders together, therefore are coupling constraints within individual organizations. In view of the multitude of possible realizations of random events (e.g., uncertain processing time requirements), they are approximated by the following expected machine capacity constraints:

$$E\left[\sum_j \delta_{jkh}\right] \leq M_{kh}^f, \forall k \text{ and } h.$$ (5)
These constraints are to be satisfied in the expected sense in the core of the optimization algorithm, and to be strictly satisfied in the schedule implementation phase.

Organizational Objective Functions

As mentioned in Section 1, the manufacturers of the supply chain have a shared goal of achieving on-time product delivery, and this can be translated to minimizing order tardiness and earliness costs for scheduling individual manufacturers. In addition, the key to get reliable order delivery performance is to reduce variances of order lead times. Terms to penalize variances of order lead times are therefore added to the objective functions of individual manufacturers. In view that order completion times in an upstream manufacturer may affect the material arrival times in its downstream manufacturer and cause additional costs (e.g., tardiness costs), the upstream manufacturer should be scheduled with an aim of reducing these costs. The objective function for an individual manufacturer \( f \) is then formulated as following:

\[
J_f = E \left[ \sum_i \left( w_f \sigma^2_i + \beta_f \kappa_f + \Delta_f \sigma_f (c_f - \alpha_f) \right) \right] + \sum_i w_i \sigma^2 (c_f - \alpha_f),
\]

(6)

In the above \( T_f \) is the tardiness of \((f, i)\) and calculated as \((0, c_f - d_f)\). The term \( E_f \) is calculated as \((0, \delta_f - b_f)\), where \( \delta_f \) is the “desired beginning time.” Parameters \( w_f \) and \( \beta_f \) are nonnegative penalty coefficients. The lead time of an order \((f, i)\) is calculated as \( c_f - \alpha_f \) and the term \( \sigma^2 (c_f - \alpha_f) \) represents its variance, with \( w_f \) the corresponding penalty weight. It can be proved that for a given arrival time \( \alpha_f \), the following relationship could be satisfied:

\[
\sigma^2 (c_f - \alpha_f) = \sigma^2 (c_f).
\]

(7)

The above implies that the variances of lead times can be obtained by calculating variances of order completion times, and this will be used in the derivations of Section 4.

The term \( C_f (c_f) \) in (6) is associated with the additional costs in \( f \)'s downstream manufacturer caused by completion time of order \((f, i)\); and used for coordinating scheduling of manufacturer \( f \), with \( \Delta_f \) an integer variable which equals to one when \( f \) is an upstream manufacturer, and zero otherwise. The cost \( C_f (c_f) \) includes penalties for tardiness, earliness, and variances of lead times, and can be obtained by a coordination technique presented in Section 4.

3.3 Cross-organization Relationship

The operations of manufacturers are linked through precedence relationship, which states that the required material or component parts for a downstream manufacturer arrives only after they have been processed in an upstream manufacturer possibly plus a required slack time (representing, e.g., transportation time), therefore following precedence constraints should be satisfied:

\[
c_f + s_f \leq \alpha_f.
\]

(8)

These constraints described the relationship between upstream and downstream manufacturers, and are cross-organization constraints.

3.4 Overall Objective Function

The objective function of the entire supply chain is to minimize the sum of individuals' cost functions:

\[
J = \sum_f J_f,
\]

subject to constraints within the organizations (1), (2), (3) and (5), and cross-organization precedence constraints (8). The decision variables are operation beginning times within all manufacturers. The problem formulation is order-wise additive, and this motivates a Lagrangian relaxation based decomposition approach.

4. SOLUTION METHODOLOGY

To solve the overall problem, one way is to relax the coupling constraints within and across the organizations (i.e., expected machine capacity constraints and cross-organization precedence constraints) to obtain order-level subproblems. The scheduling of subproblems is coordinated in a centralized manner by an iterative price-updating process, which requires information sharing among all manufacturers. In view of the amount of information involved and the proprietary nature of such information, a new approach is developed to optimize and coordinate individual manufacturers with limited communication requirements. The key idea is to view manufacturers as autonomous and cooperating decision-makers and formulate individual organization-level problems. Lagrangian relaxation is used to relax expected machine capacity constraints to further decompose a manufacturer problem into multiple order-level subproblems. These subproblems are effectively optimized by using stochastic dynamic programming (SDP, [6] and [10]), with a new variance control technique introduced to calculate and reduce variances of order lead-times without excessive computational requirements. The scheduling of individual manufacturers is coordinated based on updated information obtained from scheduling of their upstream or downstream manufacturers, and uncertainties associated with individuals’ scheduling can be effectively captured and propagated across a chain without excessive information flow.

4.1 Cross-organization Coordination

The coordination of individual manufacturers is performed based on information from their upstream or downstream manufacturers, e.g., the schedule of an upstream manufacturer provides parameters (e.g., mean and variance) of the component part arrival time distributions for its intermediate downstream manufacturer, and the schedule of a downstream manufacturer provides for its supplier (i.e., the upstream manufacturer) information about additional costs caused by the schedule of the upstream manufacturer. In this way, individual manufacturers are scheduled without excessive iterative information flow as in the centralized coordination to satisfy cross-organization precedence constraints while optimizing overall performance, and uncertainties and costs associated with individual
manufacturers are effectively captured and propagated across the chain. Furthermore, in view that the process is similar to the way of centralized coordination, convergence should be achieved.

4.2 Scheduling Individual Manufacturers

To schedule a manufacturer, the problem is to minimize the objective function (6) subject to constraints within the organization (1), (2), (3) and (5). For illustration purpose, let $f$ denote the last manufacturer in the chain, therefore it has no downstream manufacturer while its expected material arrival times $\{a_l\}$ are assumed to be given and obtained from its upstream manufacturer $f-1$ by coordination. Within the LR framework, the expected machine capacity constraints (5) are relaxed by using multiplier $\pi_{kh}$, and the relaxed problem is given by:

$$
\min L_f, L_f = E\left[\sum_{i} w_f \pi_f + \beta_f \bar{E}_f\right] + \sum w^o(\sigma_i) \\
+ \sum_{i} \pi_{kh} \sum_{k} E(\delta_{fkh}) - M_{kh}
$$

subject to (1), (2) and (3) for all orders. The term $\Delta \bar{C}_{bf}(c_l)$ is omitted from (6) in view that $f$ is the last manufacturer, and for simplicity of presentation, subscript $f'$ is dropped in the following derivations. In view that $\{a_l\}$ are given, the variance penalties in (10) are variance penalties on order completion times from (7). The relaxed function is thus decomposed into following individual order subproblems:

$$
\min L_{f_i}, L_{f_i} = E\left[w_i \bar{T}_i + \beta_i \bar{E}_i + \sum_{k} \pi_{kh} \sum_{k} E(\delta_{fkh}) - M_{kh}\right] + w^o(\sigma_i),
$$

subject to (1), (2), and (3). The decision variables are order operation times for the order. To solve the subproblem by using SDP, the challenge is to efficiently propagate order completion variances from the last stage backwards. This is difficult in view that order completion times themselves are results of the optimization process. To address this difficulty, a novel variance control technique is introduced below. The key is to view the completion time of a particular order given the preceding operation's completion time as the sum of the operation processing time, the required slack time, and queue time, which is obtained by optimization. Therefore operation completion variances can be calculated by variances of operation processing times and queue times in an operation-wise manner during the backward SDP process as illustrated below.

Consider a simple two-stage problem where order $i$ is going through stages 1 and 2 sequentially. For stage 1, there are two possible processing times denoted by $p_{11}$ and $p_{12}$. Similarly, stage 2 has two possible processing times $p_{21}$ and $p_{22}$. It is assumed that these times are independent. For simplicity of illustration, the required slack times are assumed zero for remaining derivations. In SDP, a stage corresponds to an operation, and a state corresponds to a possible beginning time as shown in Figure 2:

![Figure 2: The schematic of backward SDP for a two-stage scheduling problem](image)

The algorithm starts with the last stage: given a particular beginning time $b_{12}$, order completion time (i.e., $c_{12}$) can be obtained for each possible processing time (e.g., $p_{12}$). The terminal cost associated $b_{12}$ is thus calculated as:

$$
V_{12}(b_{12}) = E\left[w_{12} \bar{T}_{12} + \sum_{k} \pi_{kh} \sum_{k} E(\delta_{fkh}) - M_{kh}\right] + w^o(\sigma_i)
$$

subject to non-negativity of all multipliers. To solve (16), the “Surrogate Subgradient Method” (SSGM) ([11]) is used allowing efficient resolution of large problems.
It should be noted that the above derivation can be extended to more complicated process plans, and to cases with stochastic arrival times.

The optimal cumulative costs \( L^* \) in (15) is associated with selections of order beginning times, and is linked to order completion times of \( f_j \)'s upstream manufacturer through cross-organization precedence relationship (8) and arrival time constraints (3). These costs can be sent back to the upstream manufacturer to be used in place of \( C_d(c_j) \) in (6) during the next cycle of scheduling. Similarly, an upstream manufacturer can be scheduled in the same way as presented above, and provides information about predicted component part arrival time for its downstream manufacturer. The uncertainties associated with scheduling are captured by scheduling within individual manufacturers and propagated across the entire chain by coordination, and the variances of product lead times, which can be approximated by summation of order lead times within individual manufacturers, are effectively reduced through individual scheduling processes and coordination across the chain.

4.3 Schedule Implementation and Performance Evaluation

The solutions of individual organizations, when put together, are generally not implementable in view that the machine capacity constraints (4) are approximated by their expected versions and relaxed by Lagrangian multipliers, and activities of organizations are synchronized with limited information flow and coordination. A greedy heuristics ([10]) are used at the on-line implementation phase to eliminate possible constraint violations. To evaluate algorithm performance, schedules are tested by using a simulation model embedded with the above-mentioned heuristics. Based on the simulation results, the expected order lead-times can be estimated by its sample mean with associated sample variance. The performances of different algorithms can be compared by using simulations with the same set of random seeds.

5. NUMERICAL RESULTS

The method presented above has been implemented in Matlab and tested on a PC with a Pentium IV 2.0 GHz processor and 512M SDRAM. Two examples are tested, and the first example is for a single job shop scheduling problems with fifty orders, where cases with varying settings of penalty weight \( w^* \) are examined to evaluate the effectiveness of the new approach to reduce variances of order lead times. In addition, the performances of the method are evaluated by cases where variances of uncertain parameters (e.g., material arrival times and operation processing times) are set to be low and high to represent different uncertainty levels. The second example presents the results of solving a two shop scheduling problem. The performance of the coordination technique is compared with that of a centralized coordination approach, which allows unlimited information sharing and coordination among manufacturers.

For all the cases, the Surrogate Subgradient (SSG) method is used to update the multipliers. Algorithms are terminated after a fixed amount of computation time. Based on the scheduling policy obtained, fifty simulation runs are conducted for each case.

Example 1. In this example, fifty orders with 300 operations are to be scheduled on 60 machines of 6 types of one job shop. The orders arrive randomly in-between day 5 and day 25. For simplicity, all orders have a required final delivery date equaling the expected order arrival time plus 0.1 days. The tardiness, earliness weights are set to be 1 and 0.1, respectively. The results are summarized in Table 1 and Table 2, where the variances of uncertainty parameters are set to be 1.6 for Table 1, and 3.2 for Table 2 to represent low and high uncertainty levels, respectively. For each table, three cases are tested. For Case 1, results are obtained by using the traditional Lagrangian Relaxation (LR) method, in which the object function is formulated similar to (6) but without the extra penalty terms associated with variance of lead times. For Case 2 and Case 3, the new LR approach with variance control technique are used with penalty weight \( w^* \) set to be 3 for Case 2 and 5 for Case 3.

In the tables, the term "Average Order Lead Time," "Average Total Tardiness and Earliness Cost" are average results for all orders calculated based on fifty simulations. Similarly, the "Variance of Lead Times" is the average variance of lead times for all the orders. The "CPU time" is the computation time for running the LR based algorithms for each case.

### Table 1. Performance comparisons approach when uncertainty level is low

<table>
<thead>
<tr>
<th>Compared Items</th>
<th>Case 1 Traditional LR/SSG</th>
<th>Case 2 LR/SSG ( w^* = 3 )</th>
<th>Case 3 LR/SSG ( w^* = 5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Order Lead Time</td>
<td>49.77</td>
<td>48.81</td>
<td>48.11</td>
</tr>
<tr>
<td>Variance of Lead Time</td>
<td>12.40</td>
<td>9.27</td>
<td>8.87</td>
</tr>
<tr>
<td>Average Tardiness and Earliness Cost</td>
<td>20.74</td>
<td>21.62</td>
<td>33.08</td>
</tr>
<tr>
<td>Percentage of Late Delivery</td>
<td>6.24%</td>
<td>4.96%</td>
<td>5.40%</td>
</tr>
<tr>
<td>CPU time (Sec)</td>
<td>211</td>
<td>212</td>
<td>211</td>
</tr>
</tbody>
</table>

### Table 2. Performance comparisons approach when uncertainty level is high

<table>
<thead>
<tr>
<th>Compared Items</th>
<th>Case 1 Traditional LR/SSG</th>
<th>Case 2 LR/SSG ( w^* = 3 )</th>
<th>Case 3 LR/SSG ( w^* = 5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Lead Times</td>
<td>54.24</td>
<td>49.37</td>
<td>49.49</td>
</tr>
<tr>
<td>Variance of Lead Times</td>
<td>27.24</td>
<td>21.29</td>
<td>20.11</td>
</tr>
<tr>
<td>Average Total Tardiness and Earliness Cost</td>
<td>29.98</td>
<td>29.72</td>
<td>38.28</td>
</tr>
<tr>
<td>Percentage of Late Delivery</td>
<td>8.60%</td>
<td>5.40%</td>
<td>6.52%</td>
</tr>
<tr>
<td>CPU time (Sec)</td>
<td>212</td>
<td>212</td>
<td>213</td>
</tr>
</tbody>
</table>

From the tables, it can be shown that the new approach outperforms the that of the traditional LR method (i.e., Case 1 versus Case 2 in both tables) by effectively reducing the average order lead times as well as its variance and achieving lower rate of late delivery without drastic increasing of the
average tardiness and earliness cost. The improvements are more significant when uncertainty level is high, which implies the new approach can be used in a highly stochastic manufacturing environment to achieve reliable on-time deliveries. It is also shown that by increasing the penalty weight \( w' \) (i.e., Case 2 versus Case 3 in both tables), the variances of lead times can be reduced more significantly while the average total costs may increase, and so does the rate of late delivery. A high value of \( w' \) implies that more emphasis is put on delivery reliability, and this may be achieved at the price of increasing tardiness and earliness cost. Therefore selecting an appropriate value for \( w' \) is critical to achieve reliable on-time delivery and low tardiness and earliness cost.

**Example 2.** In this example, 600 operations associated with 100 orders are to be processed on 108 machines of 6 types in two shops in a sequential manner. The orders arrive randomly at the first shop in-between day 5 and day 35. All the orders have a required final delivery date equaling expected order arrival time plus a common lead time of 65 days. The variances of uncertainty parameters are set to 1.6. The tardiness and earliness weight are set to 1 and 0.1, respectively. Three cases are tested. For Case 1, coordination are performed in a centralized way, where full information sharing is allowed by converting the problem into a single job shop scheduling problem, which is scheduled by using the new approach with variance control technique (\( w'=3 \)). For Case 2, shops are scheduled individually by using the new approach (\( w'=3 \)) and the new coordination technique is used. Case 3 is similar to Case 2, the difference is that traditional LR method are used in Case 3 (i.e., variance control technique is not used) to schedule individual shops. For Case 2 and Case 3, key scheduling information is exchanged and updated between the two shops for decision adjustment every thirty LR/SSG algorithm iterations. The results are summarized in Table 3:

<table>
<thead>
<tr>
<th>Compared Items</th>
<th>Case 1 Centralized New LR/SSG</th>
<th>Case 2 Distributed New LR/SSG</th>
<th>Case 3 Distributed Traditional LR/SSG</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Lead Times</td>
<td>60.24</td>
<td>61.83</td>
<td>63.78</td>
</tr>
<tr>
<td>Variance of Lead Times</td>
<td>37.89</td>
<td>39.26</td>
<td>48.97</td>
</tr>
<tr>
<td>Average Total Tardiness and Earliness Cost</td>
<td>332.15</td>
<td>367.63</td>
<td>393.38</td>
</tr>
<tr>
<td>Percentage of Late Delivery</td>
<td>6.19%</td>
<td>7.38%</td>
<td>9.53%</td>
</tr>
<tr>
<td>CPU time (Sec)</td>
<td>443</td>
<td>445</td>
<td>441</td>
</tr>
</tbody>
</table>

From the table, it can be seen that the performance of the new approach in Case 1 is better than that in Case 2 with lower average tardiness and earliness cost and percentage of late delivery. This can be explained by the fact that unlimited information sharing and coordination can be achieved by centralized coordination in Case 1, while in Case 2, scheduling of individual shops are performed based on limited information exchanged between two shops. However, the new coordination technique is effective by providing comparable performance with respect to that of Case 1 without drastic increasing of total tardiness and earliness cost and percentage of late delivery. In addition, the effectiveness of the variance control technique in scheduling multiple-manufacturer problems are demonstrated by the comparison of Case 2 and Case 3, where the new approach outperform traditional LR/SSG method significantly.

6. CONCLUSIONS

In this paper, a novel variance control technique is developed to improve supply chain delivery performance by accurately estimating and effectively reducing variances of lead times through scheduling within individual members as well as through coordination across a chain. Testing results supported by simulation demonstrates that by reducing the variance of lead times, reliable delivery with short product lead times could be achieved without drastic increasing of the total cost. The effectiveness of the new approach is more significant when manufacturing activities is subject to high level of uncertainties, and this is of significance for practical applications.

7. ACKNOWLEDGEMENT

This work was supported in part by the National Science Foundation grant DMI-0223443.

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