Manufacturing System Modeling for Productivity Improvement

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Abstract

Competition and the drive for profits are forcing companies to implement various productivity improvement efforts. Implementation of total productive maintenance (TPM) techniques has led to significant productivity improvements for individual equipment, particularly in the semiconductor industry. The productivity improvements achieved at the equipment level are significant but insufficient because what a company really needs is a highly efficient system/factory. This is especially true in the discrete manufacturing industry. In this paper, an approach, based on overall equipment effectiveness (OEE), is developed to model the productivity of a manufacturing system in terms of overall throughput effectiveness (OTE). Sensitivity analysis and theory of constraints are used to help identify productivity improvement opportunities. A real-world case study is presented to illustrate the applicability of the approach.

Keywords: Manufacturing System, Productivity, Modeling, Overall Equipment Effectiveness

1. Introduction

Keeping ahead of the game is tougher than ever in today’s manufacturing industries. Competition is worldwide, and markets are fast becoming price sensitive. These challenges are forcing companies to implement various productivity improvement efforts to meet the needs of ever-changing market demand. The total productive maintenance (TPM) paradigm, launched by Nakajima (1988) in the 1980s, has provided a quantitative metric for measuring the productivity of an individual production component (equipment, machine, tool, process, etc.) in a factory. This metric, which is called overall equipment effectiveness (OEE), is becoming widely accepted. Specifically, it has been routinely used as a quantitative tool essential for measurement of productivity in semiconductor manufacturing operations.

However, quantitative OEE analysis is still in the early stages of development. Currently, it is limited to productivity behavior of individual equipment. Metrics for measuring and analyzing the productivity of manufacturing operations from the equipment level to the system level are of increasing importance to companies seeking to continuously optimize existing operations. Recent publications by Scott (1999) and Scott and Pisa (1998) recognize and analyze the need for a coherent, systematic methodology for productivity measurement and analysis at the system (factory) level. Due to advances in manufacturing technology, manufacturing systems and processes are becoming complex and are increasingly characterized by high levels of automation and integration, greater demands on performance, and various forms of human supervisory control. Understanding the productivity of a system typically involves the analysis and understanding of the complex layout and interconnection of many pieces of equipment. Hence, the modeling and analysis of productivity for complex manufacturing systems/factories has become a challenge for engineers and academic researchers.

Due to the complex nature of most manufacturing systems, at present it is still very difficult to analyze the overall performance of a complex manufacturing system. This paper proposes a new approach to model the performance of a manufacturing system and identify the problems and underlying improvements needed to increase productivity, using as inputs the OEE and other parameters describing
individual production components making up the system. Two key system metrics are employed. The first one is overall throughput effectiveness (OTE), which is the ratio of actual throughput to theoretical throughput. The second metric is cycle time effectiveness (CTE), which is the ratio of theoretical cycle time to actual cycle time. Based on the approach, a software tool is developed to analyze the performance of production systems in terms of OEE, OTE, and CTE. It is used as a supporting tool for identifying productivity improvement opportunities, based on the Theory of Constraints (TOC).

2. Literature Review

Two preparatory works should be carried out before identifying opportunities of productivity improvement. One is to model the manufacturing system, including its production equipment and the overall process flows. The other is to measure the productivity of individual equipment in the manufacturing system, as well as the whole system. This section gives a summary of current status of these two research issues.

2.1 Manufacturing System Modeling

During the last two decades, attempts have been made to model, analyze, and design different aspects of manufacturing systems. Modeling methods reported in the literature include the following:

- **Graph with Results and Actions Interrelated (GRAI)** is based on a conceptual reference model that uses two graphical tools and a structured approach. In this conceptual representation model, a manufacturing system is decomposed into three subsystems: physical system transforming raw materials into products; decision system managing and/or controlling the physical system; and information system offering assistant information (Carrie and Macintosh 1997; Chen, Vallespir, Doumeingts 1997; Doumeingts 1985).

- **Integrated computer-aided manufacturing DEFINition (IDEFO)** is a function modeling language consists of a hierarchy of diagrams, text, and glossary. The diagram is the major component of an IDEFO model. It presents a manufacturing system in forms of boxes that are organized hierarchically. These boxes are linked with arrows, which represent data or object interfaces. The attachment position between arrow and box indicates four interface types, i.e., Input, Control, Output, and Mechanism/resource (ICOM) (Cheng-Leong, Pheng, Leng 1999; Ang 1999; Colquhoun, Baines, Crossley 1993).

- **Structured Analysis and Design Technique (SADT)** uses a number of graphical tools, including diagrams, actigrams, datagrams, node lists, and data dictionaries. Two types of elements, activities, and data, are contained in a diagram. An actigram describes the relationship between activities elements, and a datagram describes the relationship between data elements (Santarek and Buseif 1998; Zaytoon, Niel, Mille 1994; Down, Clare, Cuc 1988).

- **Structured Systems Analysis and Design Method (SSADM)** provides interfaces between the method procedure and techniques. With SSADM, a system can be broken down into modules. A module contains various activities steps. Each step in it has several tasks with inputs and outputs (Toh 1999, Ashworth 1988).

In addition to these formalized modeling methods, a number of other tools were also used in manufacturing system modeling. For example, Zimmermann and Hommel (1999) proposed a new class of colored Petri nets for modeling the structure and work plans of a manufacturing system. After simulating the modeled system, the degree of use of workstations, or their availability, can be evaluated. Wong, Mak, and Lau (1999) developed an extended object-oriented model to describe system behaviors. Generic object types were identified for representing general concepts in a manufacturing system, including SystemObject, KnowledgeObject, Event, Operation, etc. EXPRESS-G, a subset of the STEP EXPRESS language, was also tested by some researchers (Giachetti 1999). EXPRESS-G is in fact a standard graphical notation for better understanding large information models, by showing relationships and structure of a system.

In general, all these methods have advantages and disadvantages in modeling manufacturing systems. They can identify major elements of the system and model it in a hierarchical structure by breaking down the whole system into low-level units of a factory. Flows of material, control, and information can also be simulated. However, as mentioned by some
researchers, these methods are “no more than static graphical representation” (Al-Ahmari and Ridgway 1999). Although this argument was not sufficiently justified, it can be said that, for modeling a real-world manufacturing system, a general structure is not enough.

In addition, these modeling techniques are not designed to facilitate productivity measurement and analysis. Rather, they focus on the availability of the unit/equipment, which is only one aspect of the system performance. Giachetti (1999) addressed the importance of incorporating the manufacturability issue into information modeling. He proposed a STEP EXPRESS approach to capture physical resources as well as the behaviors of the equipment, tools, and fixtures employed in a manufacturing system. However, his research still remained in a conceptual stage. Moreover, manufacturability is the system’s capability constraints and is not sufficient to measure a systems’ real performance. Integrative productivity metrics, such as Overall Equipment Effectiveness (OEE) and Cycle Time Effectiveness (CTE), are needed to accurately measure the system’s performance.

2.2 Overall Equipment Effectiveness and Cycle Time Effectiveness

OEE has been widely used by manufacturers to determine productivity at the equipment level. OEE is usually formulated as a function of a number of mutually exclusive components such as availability efficiency, performance efficiency, and quality efficiency in order to quantify various types of productivity losses, such as breakdown, setup and adjustment, idling and minor storage, reduced speed, and quality defect and rework (Nakajima 1988).

The conventional formula for OEE can be written as follows:

\[
OEE = A_{\text{eff}} \times P_{\text{eff}} \times Q_{\text{eff}} \tag{1}
\]

\[
A_{\text{eff}} = \frac{T_U}{T_T} \tag{2}
\]

\[
P_{\text{eff}} = \frac{T_P}{T_U} \times \frac{R_{\text{avg}}^{(a)}}{R_{\text{avg}}^{(h)}} \tag{3}
\]

\[
Q_{\text{eff}} = \frac{P_s}{P_a} \tag{4}
\]

where

\[
A_{\text{eff}} = \text{Availability Efficiency (Associated losses include nonscheduled downtime, breakdowns, setup and adjustments, etc.)}
\]

\[
P_{\text{eff}} = \text{Performance Efficiency (Associated losses include idle, reduced speed, blockage, etc.)}
\]

\[
Q_{\text{eff}} = \text{Quality Efficiency (Associated losses include defects, rework, etc.)}
\]

\[
T_U = \text{Equipment uptime}
\]

\[
T_T = \text{Total time of observation (After this, the actual performance of an equipment or a system can be compared with its actual situation)}
\]

\[
T_P = \text{Equipment production time}
\]

\[
R_{\text{avg}}^{(a)} = \text{Average actual processing rate during equipment in production for actual product output}
\]

\[
R_{\text{avg}}^{(h)} = \text{Average theoretical processing rate for actual product output}
\]

\[
P_g = \text{Good product output from equipment during } T_T
\]

\[
P_a = \text{Actual product units processed by equipment during } T_T
\]

Because equipment might not process at its theoretical speed during \( T_P \), thus \( R_{\text{avg}}^{(a)} \) can be determined by

\[
R_{\text{avg}}^{(a)} = \frac{P_a}{T_P} \tag{5}
\]

Using Eqs. (1) through (5) leads to another useful expression for OEE, which is

\[
OEE = \frac{P_g}{(R_{\text{avg}}^{(h)})(T_T)} \tag{6}
\]

In Eq. (6), the denominator \((R_{\text{avg}}^{(h)})(T_T)\) is the theoretical actual product output (units) in total time \( T_T \). Therefore, OEE is the good product output (units) produced by equipment in total time observed divided by the actual product output (units) that should have been produced according to theoretical processing rate in total time observed.

Another component that appears when analyzing productivity of equipment is the time factor. When inventory buffers precede or follow equipment, the cycle time or manufacturing lead time becomes a concern. As the inventory level builds in buffers, the time elapsed before a product is delivered from the machine increases. Cycle time effectiveness (CTE) is the metric that compares actual equipment cycle time to the theoretical cycle time taking into account the inventory buffers that may or may not exist. Here, cycle time of a unit is defined as the elapsed time

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between the arrival of a product at the unit and the departure of the product from that unit. Then CTE can be defined as follows:

$$CTE = \frac{CT_{th}}{CT_a}$$  \hspace{1cm} (7)$$

where $CT_{th}$ stands for the theoretical cycle time, and $CT_a$ for the actual cycle time, which can be determined by total equipment use time divided by the number of products produced.

Research on improving the productivity of individual pieces of equipment using OEE is not new (Somekh 2000, European Semiconductor 2001). However, the question is what kind of “averaging” or “normalizing” method should be applied to OEE values from all pieces of equipment to derive the factory-level metric representing factory productivity relative to the factory’s maximum capability. This question was raised by industrial practitioners, but no answers are available in the literature. It is addressed in this paper. Details of the methodologies proposed for evaluating factory-level productivity, recognizing subsystems, and improving the productivity through simulation, will be discussed individually in the following section.

3. Methodology

For the purpose of productivity improvement, a well-defined modular modeling approach is proposed. The building block of a manufacturing system is a unit production process (UPP), rigorously defined as shown in Figure 1. The architectural combinations of UPPs are based on Burbidge’s classification methodology (Burbidge 1994, 1992, 1990). A unit factory (UF) can always be decomposed into these basic architectural combinations. Productivity metrics for a UF, including overall throughput effectiveness (OTE) and system cycle time effectiveness (CTE), can thus be derived based on overall equipment effectiveness (OEE) of individual UPPs.

3.1 Manufacturing System Productivity Metrics

There are five major “types” of unique UPP combinations or subsystems: “series,” “parallel,” “assembly,” “expansion,” and “complex,” with the provision that “rework” can be applied as a modification of each of the basic subsystems, for example, a series subsystem with rework. Among these architectural combinations, series and parallel combinations are frequently encountered in real-world manufacturing systems. Moreover, other types of combinations can be deduced from the two fundamental types. Therefore, formulas are presented for calculating OTE and CTE for the cases of series and parallel combined UPP subsystems using the following notation:

$$\begin{align*}
n & \quad \text{Number of UPPs in the subsystem} \\
T_R & \quad \text{Total time of observation}
\end{align*}$$
$P_{GF}$  Good product output (units) of the subsystem
$P_{TH(F)}$  Theoretical product output (units) of the subsystem
$R_{THA(F)}$  Theoretical average processing rate of the subsystem
$R_{THA(i)}$  Theoretical average processing rate of ith UPP
$P_{g(i)}$  Product output (units) of ith UPP (including good products and scraps)
$P_{g(i)}$  Good product output (units) of ith UPP
$CT_{th(i)}$  Theoretical cycle time of ith UPP
$C_{ar(i)}$  Product transportation time from previous UPP to ith UPP

In a series combined subsystem, the theoretical average processing rate is the theoretical processing rate of the slowest UPP, that is, $R_{THA(F)} = \min\{R_{THA(i)}\}$, $i = 1, 2, ..., n$. Therefore,

$$O_T^{series} = \frac{P_{GF}}{R_{THA(F)}} = \frac{P_{g(n)}}{R_{THA(F)}} = \frac{P_{g(n)}}{\min_i(R_{th(i)})}$$  \hspace{1cm} (8)

This equation can be derived further to obtain the following:

$$O_T^{series} = \frac{P_{g(n)}}{\sum_{i=1}^{n} OEE_i (T_T)}$$  \hspace{1cm} (9)

When the system is operating in a steady state, good product output at each UPP will be approximately equal, that is, $P_{g(1)} \approx P_{g(2)} \approx ... \approx P_{g(n)}$. Under such circumstances, $O_T^{series} = \max \{OEE_i\}$. This means that the UPP with the highest OEE is a key element that dictates the overall performance of the system. Such a UPP is regarded as a bottleneck of the system due to the following reasons: (1) the UPP has the slowest processing rate (this is the reason that it needs a high OEE to keep up with the system's material flow), and (2) the breakdown of such a UPP will certainly disrupt the production (throwing it out of steady state, causing upstream inventory build up, and downstream machine starvation), leading to a significant drop of the system performance (OTE number). To ensure high system performance, special attention is needed when making decisions regarding such a UPP.

In a parallel combined subsystem, the theoretical average processing rate is the summation of the theoretical average processing rate of each UPP in the subsystem, that is, $R_{THA(F)} = \sum_{i=1}^{n} R_{th(i)}$. Therefore,

$$O_T^{parallel} = \frac{P_{GF}}{P_{TH(F)}} = \frac{\sum_{i=1}^{n} OEE_i (R_{th(i)}) (T_T)}{\sum_{i=1}^{n} R_{th(i)}}$$  \hspace{1cm} (10)

Equation (7) can be directly used to calculate CTE for UPP subsystems when the actual cycle time is measured and the theoretical cycle time is calculated. The theoretical cycle time for a series combined subsystem is determined by the following:

$$CT_{th(i)} = \sum_{j=1}^{n} CT_{th(j)} + \sum_{j=2}^{n} C_{ar(i)}$$  \hspace{1cm} (11)

In a parallel combined subsystem, for various products the time between arrival and departure may be different because the products can choose different paths in the subsystem. Therefore, an average of all theoretical cycle time for producing all products in certain UPP subsystems is used as the theoretical cycle time; that is:

$$CT_{th(F)} = \frac{\sum_{i=1}^{n} P_{th(i)} (CT_{th(i)})}{\sum_{i=1}^{n} P_{th(i)}}$$  \hspace{1cm} (12)

### 3.2 Algorithm for Subsystem Identification

The interconnectivity of a manufacturing system can be represented as a directed graph using the following representation:

- A UPP $i$ is represented as a vertex $V_i$, where $i = 1, 2, ..., n$, $n$ is the number of the UPP in the manufacturing system.
- If parts flow from UPP $i$ to UPP $j$, then there is a directed edge from $V_i$ to $V_j$. 

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An algorithm, shown in Figure 2, is developed to automatically recognize UPP subsystems based on graph theory. Details of the two shaded boxes in Figure 2 are public knowledge in the graph theory literature and hence are not explained further. The type of merged vertices is always regular, whose productivity measures are calculated using equations derived in Section 3.1. Note that this algorithm detects not only series combined subsystems and parallel combined subsystems but also assembly combined subsystems and expansion combined subsystems.

3.3 Productivity Improvement
The Theory of Constraints (TOC), created by Goldratt (Dettner 1997), introduced a methodology with a five-step cycle for dealing with variables levels of constraints that restrain the system from achieving
desired manufacturing excellence. Razzak (2001) has shown that combining the five-step TOC cycle with the developed metrics provides a powerful tool for managing productivity improvement activities. The proposed improvement methodology is a systematic process comprising 12 steps grouped into four categories associated with various phases of implementing the productivity improvement strategy. Figure 3 is a schematic representation of the improvement cycle.

The first phase is referred to as the preparatory stage. Four steps are included as follows:

1. **Flowchart system architecture**: allocate beginning and ending UPPs to specify system boundaries; lay out all UPPs and identify their interconnectivity; recognize subsystems based on material flow.
2. **Define productivity parameters**: determine production characteristics of each UPP (ideal processing rates, buffer levels, production capacity, and transportation rates to and from UPPs); assign time intervals for measurement frequency.
3. **Apply productivity metrics and algorithms**: implement calculation algorithms based on the productivity metrics.
4. **Collect data**: obtain data through online data acquisition or from production reports.

The second phase, Step 5, is to calculate the productivity metrics at the equipment [each UPP (OEE and CTE)], subsystem, and system levels.

In the third phase, root-cause analysis is carried out for determining the type and location of losses throughout the system. There are two separated steps in this phase:

6. **Allocate bottleneck and identify losses**: identify system bottleneck as the UPP with the highest OEE in a series combined subsystem; evaluate bottleneck productivity by analyzing $A_{\text{eff}}$, $P_{\text{eff}}$, and $Q_{\text{eff}}$; determine losses at the bottleneck.
7. **Identify upstream and downstream losses**: analyze losses occurring at UPPs upstream and downstream from the bottleneck, respectively.

Finally, results from the previous steps are integrated with sensitivity analysis to enhance system productivity. Five steps are needed in this final phase:

8. **Identify constraint**: based on information from steps 6 and 7, determine the constraint responsible for the limitation on system productivity.
9. **Decide how to relieve constraint**: perform sensitivity analysis by using simulation to assess various improvement scenarios.
10. **Manage improvement decision**: determine priorities of improvement tasks based on simulation results. This step involves the organizational culture in exploiting the improvement tasks by subordinating everything else in the system to accomplish productivity improvement.
11. **Eliminate constraints**: execute improvement tasks.
12. **Find new constraints**: repeat the cycle by finding new constraints for continuous productivity improvement.

Repeating the four-phase cycle takes one of two different paths depending on the improvement implemented. If no changes are required in the system design, then the cycle may be repeated starting from phase 2. On the other hand, if improvement introduces a change to the system design, the cycle should be repeated from phase 1.

4. **Prototype Software Tool Overview**

Based on the methodology proposed, a prototype software tool was developed to facilitate the execution of the productivity improvement methodology. The operating steps are presented in the Case Study section. This section describes three major func-
tions of the software tool. They are: (1) electronic flowcharting to represent the system model, (2) production data acquisition for theoretical and measured parameters of the system and its UPPs, and (3) productivity calculation and display.

(1) Electronic Flowcharting

After identifying the target production line (manufacturing system) and its system boundaries, the user may flowchart the system by specifying all the production units (equipment) involved. The user would decide on the material flow linking between the production units to form the architectural layout of the manufacturing system. This feature allows a manufacturing company to quickly analyze as many production lines as it wants. Another advantage of this feature is the ability to easily incorporate any system design changes, such as introducing new equipment into the system based on improvement decisions.

(2) Production Data Acquisition

The next step is to enter the appropriate production parameters, which can be classified into two sets. The first set includes theoretical or ideal performance parameters and production system specifications, such as total production time period, theoretical UPP (unit production process) processing rate, or cycle time. Information in this set is entered only once for a production line as long as no system changes are introduced. The data entry should be done by the user, who may refer to process documents or production plans for information.

The second set of measured parameters is specific to the time period under study and includes actual production data, such as UPP downtimes, UPP quality losses (yield), UPP actual processing rate or cycle time, and UPP average processing rates. Information in this set changes for every production time period. The data entry can be either manual or automatic. Manual data acquisition does not necessarily mean having the user physically enter every single number from production report sheets. It could be in the form of importing data from readily available production reports that are saved in a computer database. Automatic data acquisition is more convenient. It means interfacing the software tool with automatic data acquisition system (if such a system is deployed in the production line) for real-time data collection.

(3) Productivity Calculation and Display

The determination of UPP level productivity (OEE, CTE, availability efficiency, performance efficiency, and quality efficiency) from the collected data is straightforward. To determine the productivity of the production line, it is necessary to identify its architectural configuration first. Different subsystem combinations are automatically recognized based on the algorithm presented in Section 3.2. Equations developed in Section 3.1 are then used to calculate system-level productivity. A bar chart is then displayed with information on both system-level and individual equipment productivity to facilitate improvement analysis.

5. Case Study

A real-world industrial case study was conducted using a production line from a leading glass manufacturer, Pilkington North America. Detailed description of the operations for the case study can be found in Razzak (2001) and Huang et al. (accepted). For confidentiality reasons, actual names of the production equipment are not used. Major steps are summarized as follows.

First, the electronic flowchart of the production line is shown in Figure 4. It is created by adding the UPPs from the Add option in the UPP pull-down menu. The UPPs are then lined up to match the actual architectural layout of the facility. After adding all UPPs, the user then determines the material flow path within the system by linking UPPs.

Second, clicking on any UPP will activate the data input template. The user may enter the data interactively. For the first UPP (named Ma), the data input template is shown in Figure 5. With the collected data, the availability efficiency, performance efficiency, and quality efficiency can be calculated. The product of these three efficiency values is the OEE of the UPP. The OEE of UPP Ma is calculated as 0.51 as shown in Figure 5. Note that data entered in the first two steps can also be imported from an Excel file or an Access file. The software automatically read data from the data file and displays the system model on the screen.

Third, selecting Calculate from the Compute menu gives the final results of system productivity. For the time period of study for the production line, OTE was calculated to be 0.66, while CTE was 0.68. Results of OEE from all UPPs, in addition to
OTE and CTE, are then displayed through a bar chart as seen in Figure 6. In the chart, the bar with the number 13 corresponds to UPP II, as named in the electronic flowchart of Figure 4. Visual inspection reveals that this is the UPP with the highest OEE, and it is an element of a series combined subsystem. This result suggests that II is the UPP with the most activity among all UPPs in the system. It may also be concluded based on the fact that this UPP has the slowest operating rate or speed. Therefore, UPP II is considered to be the bottleneck that dictates the amount of material that may be produced by the system.

Based on the results from the software, there is now a starting point to begin analyzing the production data to report what and where the losses are in the system. The following is a general description of tasks performed to identify bottlenecks, losses, and constraints:

1. Identify the UPP with the highest OEE (bottleneck) in a series combined subsystem.
2. Compare actual losses of quality, availability, and operating rate to the acceptable limits.
3. Save results of unacceptable losses to database.
4. Determine subsystem losses by performing Tasks 1, 2, and 3 at every UPP in the subsystem of the bottleneck.
5. Perform Tasks 1, 2, and 3 at every UPP and subsystem upstream from the bottleneck.
6. Perform Tasks 1, 2 and 3 at every UPP and subsystem downstream from the bottleneck.

Those losses recognized to be below acceptable limits are defined as the constraints holding the system from producing at the desired OTE level. In Figure 3, Step 9 is to “decide how to relieve the constraint.” This is where simulation can be beneficial. The various losses that would have been categorized as system constraints during the total production time usually have different impacts on the system as a whole. People involved in the decision making for deploying improvement tasks are challenged with questions such as “which loss elimination has the greatest impact on productivity improvement?” Simulation can help answer this question. Detailed analysis and simulation of the production line can be found in Huang et al. (accepted).

The next steps, according to the improvement methodology, are to manage the improvement
decision (Step 10) and then eliminate the constraint (Step 11). These tasks require close interaction and collaboration by manufacturing with other functions within the organization. After the decisions are implemented, the methodology is repeated for continuous improvement.

6. Conclusions

In this paper, a methodology is proposed to model manufacturing systems for productivity improvement. The underlying concept for the methodology is that a complex manufacturing system can be treated as the combination of a number of simple subsystems, which in turn are the combination of individual unit production processes (UPP). Productivity metrics (OEE, OTE, and CTE) and the Theory of Constraints are then integrated into the methodology to measure system performance and help identify productivity improvement opportunities. To demonstrate the effectiveness of the methodology, a software tool for electronic flowcharting and productivity analysis of a production system was developed and successfully tested using a real-world case study.

However, the identification of constraints and recommendation for improvement scenarios are still conducted manually. Likewise, simulation models (Huang et al., accepted) for use with the productivity improvement methodology are also currently constructed manually. Promising future research directions include: (1) determination of the complete set of UPP subsystem connectivity templates that might be used to describe all types of manufacturing systems; (2) assessment of techniques for automation of the constraint identification process; and (3) exploration of mechanisms that can automatically generate a simulation model based on an electronic flowchart and production data.

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References


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