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Fast algorithm for evaluating the similarity of manufacturing processes within a dynamic production environment

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To achieve efficient and economical production, planners and/or designers of production systems frequently must evaluate manufacturing process similarities for various products that they intend to produce. Such work is particularly important in product-mix production, which is widely used in various production systems, including product-oriented repetitive manufacturing, cellular manufacturing, and process-oriented manufacturing. A new potential application for evaluating manufacturing process similarity is necessary in dealing with capacity exchange between rush orders and prescheduled orders. Traditionally, most evaluating methods assumed an essentially static environment, and merely compared the manufacturing routing, processing time and demand. Meanwhile, other more complex evaluating methods were simply impractical. This study suggests a relatively simple but practical method for evaluating the manufacturing process similarity within a dynamic bucketed production environment. The proposed algorithm considers load projection and workstation utilization in terms of a current production schedule. Finally, a real numerical instance is cited to illustrate the effectiveness of the proposed approach.

1. Introduction

With the emergence of the age of personalized consumption, the market is no longer satisfied with a mass produced uniform product. Manufacturing firms thus must offer a variety to remain competitive. However, increased product diversity markedly raises the complexity of manufacturing environment design, and production planning and management. For instance, frequent process changeover can be a significant time, and thus cost, burden. Providing an increased choice at reduced cost thus poses significant challenges for manufacturing firms attempting to achieve or maintain competitiveness. Accordingly, firms are constantly seeking the best compromise between production efficiency and production flexibility. The product-mix production (mixed mode production) that manufactures or assembles a range of products simultaneously is one manufacturing planning technique for achieving such an optimum compromise. Presently, product-mix production is being intensively

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used in various production systems, including product-oriented repetitive manufacturing, cellular manufacturing, and process-oriented manufacturing. However, for production systems that adopt the mode of product-mix production, quality construction of mixed production batches is essential. Reduced divergence in the manufacturing processes within individual mixed production batches reduces process variation, and thus minimizes processing time, transport and set-up time, and thus total cycle time. More detailed discussion of the concepts related to product-mix production can be found in Browne *et al.* (1996), Noori and Radford (1992), and Silver *et al.* (1998).

Also, to accelerate products to market and thus seize market share as early as possible, rush orders are sometimes placed by customers of manufacturers. Consequently, facing increasingly variable customer requirements and market demand, the need for timely capacity adjustment, or rather exchanging or adjusting the manufacturing sequence for relevant orders, within a given period of time has arisen. Therefore, besides the applications mentioned above, a new potential application for evaluating manufacturing process similarity relates to capacity exchange between rush orders and prescheduled orders, based on which the orders to be exchanged are determined. In such cases, evaluation of manufacturing process similarity can help minimize the impact of production rescheduling. Specifically, such evaluation could minimize disruption to predetermined completion times and promised delivery dates for the rest of the prescheduled orders resulting from the operation of capacity exchange. Evaluation of manufacturing process similarity would allow the order with the largest degree of similarity to be exchanged with a new order. If further capacity were still required, the order with the second highest similarity score would be exchanged next, and so on. For more detailed discussion of the mechanism of capacity exchange see Chang *et al.* (2002).

Until now, little research has investigated the problem of optimal capacity exchange within the same plant, yet there is plenty of literature that describes several evaluation methods for establishing mixed production batches in accordance with manufacturing processes. Previous researchers have used the following techniques to form the part families, which are mainly organized in planning layers and based on the static environments.

(1) Matrix based methods (Kusiak 1985, Seifoddini and Wolfe 1986, Massberg and Kuenzel 1996, Al-Sultan 1997).
(2) Mathematical programming algorithms (Kusiak and Cho 1992, Tam 1990, Srinivasan *et al.* 1990, Ang and Hegji 1997, Dasari and Moon 1997).
(3) Fuzzy logic approach (Li *et al.* 1986, Lozano *et al.* 1999).
(4) Graph theory based methods (Kiang *et al.* 1995).
(5) Artificial intelligence based methods (Moon and Chi 1992, Kamal and Burke 1996, Al-Sultan and Fedjki 1997).

DeWitte (1980), Seifoddini and Wolfe (1986), Mosier (1989), Tam (1990), and Jeon *et al.* (1998) all have presented methods for calculating the similarity coefficient based on production flow, similar to the methods presented here.

In contrast, studies investigating the product-mix problem that basically belongs to the task of operation (shop floor) layer are relatively uncommon. Bahl *et al.* (1991) applied a linear programming model, which focused on meeting demand for products/spare parts with workstation capacity, to formulate the optimal product-mix decision problem. Moreover, Kasilingam (1995) designed a nonlinear programming model to do the same. Malik and Sullivan (1995) have also devoted themselves to the problem of optimizing product-mix to maximize total profits in terms of revenue and production cost for products grouped in a mixed production batch. These previous works differ from this study in the grouping criteria used for mixed production batches. Notably, Hsu and Chung (1998), and Fredendall and Lea (1997) have developed an algorithm based on TOC (theory of constraints) to solve the product mix problem. Moreover, Spedding *et al.* (1996) used simulation to investigate product mix. Finally, Seifoddini and Djassemi (1995, 1997), and Kuroda *et al.* (1997) have examined the sensitivity or flexibility of product mix variation.

However, although numerous methods have been proposed, most are either based on a static environment, and thus merely compare manufacturing routing, processing time and demand, or else they are too complex to the point of being impractical. This study suggests a relatively simple, yet feasible and practicable method for evaluating manufacturing process similarity within a dynamic bucketed production environment. More specifically, the proposed similarity algorithm described in section 2 not only is concerned with comparing manufacturing routing, corresponding workstation, and accumulated processing time at each time bucket in every workstation, but also considers such dynamic factors as load projection and workstation utilization in terms of a detailed schedule. Therefore, the manufacturing similarity defined and developed in this study could be applied to serve as a basis for helping optimally to achieve some tasks associated with operation (execution) layer. As stated above, these tasks may include managing capacity exchange for rush orders under full capacity utilization, creating mixed production batches, and so on, all of which are likely to be experienced in implementing shop floor (detailed) scheduling and dispatching in a typical job shop.

2. Algorithm of similarity

This section presents an algorithm for evaluating the similarity among products based on a manufacturing process. Schematically, the proposed algorithm compares each pair of products in turn, and involves the following stages:

(1) Count the accumulated processing time (workload) and workload differences at each time bucket in every workstation within a given planning horizon for the products being considered.
(2) For each workstation, determine the workload differences between products, where the workload differences from (1) are weighted by the corresponding load rate of the time bucket and then summed over all time buckets.
(3) For each workstation, calculate a similarity score by which the differences of workload from (2) are transformed to indicate the similarity of workload in percentage terms.
(4) For each pair of products, the similarity coefficient by which the scores from (3) are weighted is estimated based on corresponding workstation utilization, and this value is then summed for all workstations to represent the overall manufacturing process similarity.

Given the above principles, the algorithm is now described in detail.

First, notations used in the algorithm are defined as follows.

m number of time buckets within a given planning horizon.

c number of workstations.

$\rho_{i,j}$	load rate (that is, total of projected processing and set-up time for all currently scheduled orders divided by total available processing time at a time bucket) of workstation i at time bucket j.
$w_{i,j}$	weight of load rate of workstation i at time bucket j.
$p_{i,j}^{(k)}$	accumulated processing time and set-up time (workload) at time bucket j in workstation i for product k.
$\Delta p_{i,j}^{(k,l)}$	workload difference for workstation i at time bucket j between products k and l.
$d_i^{(k,l)}$	workload difference for workstation i between products k and l.
$s_i^{(k,l)}$	similarity score at workstation i between products k and l.
$\bar{\rho}_i$	average utilization of workstation i.
w_i	utilization weight of workstation i.
$s^{(k,l)}$	similarity coefficient between products k and l.

Generally, $\rho_{i,j}$ $(i = 1, 2, \ldots, c,\ j = 1, 2, \ldots, m)$ can be directly retrieved from information systems such as a Computer Integrated Manufacturing (CIM) system, a Flexible Manufacturing System (FMS), Manufacturing Executing System (MES), Production Management System (PMS), Schedule Management Module, or Manufacturing Resource Planning System (MRP II), depending on the system installed. In addition, the algorithm respectively treats the load rate of the time bucket and workstation utilization as the weightings of the similarity score and similarity coefficient. We hypothesize that workload differences likely become problematic and thus should be more unfavourable for busy time buckets and bottleneck workstations. The detailed procedure of the algorithm is as follows:

Step 1. Compute workload $p_{i,j}^{(k)}$ and $\Delta p_{i,j}^{(k,l)}$

First, the processing time at each time bucket in every workstation is accumulated according to the manufacturing process of the product, say product k. Next, the aggregated processing time $p_{i,j}^{(k)} (i = 1, 2, \ldots, c, j = 1, 2, \ldots, m)$ can be obtained, which is termed the workload at each time bucket in every workstation for product k. Then, the workload projection between two products is compared for each time bucket in workstation i. The computation used to calculate $\Delta p_{i,j}^{(k,l)}$ $(i = 1, 2, \ldots, c, j = 1, 2, \ldots, m)$ depends on the application. If the work involves mixed production batches, then the calculation is as follows:

$$\Delta p_{i,j}^{(k,l)} = \left(p_{i,j}^{(k)} - p_{i,j}^{(l)}\right)^2 \tag{1}$$

On the other hand, if the application is a rush order for product k that is attempting to obtain production capacity at the expense of a less urgent order for product l, then

$$\Delta p_{i,j}^{(k,l)} = \begin{cases} 0, & \text{if } p_{i,j}^{(k)} \le p_{i,j}^{(l)} \\ \left(p_{i,j}^{(k)} - p_{i,j}^{(l)}\right)^2, & \text{if } p_{i,j}^{(k)} > p_{i,j}^{(l)} \end{cases}; i = 1, 2, \ldots, c,\ j = 1, 2, \ldots, m. \tag{2}$$

Step 2. Calculate workload difference $d_i^{(k,l)}$

Next, the values of $\Delta p_{i,j}^{(k,l)} (i = 1, 2, \ldots, c, j = 1, 2, \ldots, m)$ are weighted by the corresponding weight of load rate of workstation i at time bucket j and summed over j, and then the summation is squared to determine the workload difference between products k and l at workstation i. That is,

$$d_i^{(k,l)} = \sqrt{\sum_{j=1}^{m} w_{i,j}\left(\Delta p_{i,j}^{(k,l)}\right)}; \; i = 1, 2, \ldots, c; \tag{3}$$

where,

$$w_{i,j} = \frac{\rho_{i,j}}{\sum_{n=1}^{m} \rho_{i,n}},$$

$$\rho_{i,j} = \frac{t_{i,j}}{T_{i,j}},$$

$t_{i,j}$ = total accumulated processing time in workstation i at time bucket j for all prescheduled orders, i.e., $t_{i,j} = \sum_k p_{i,j}^{(k)}$,

$T_{i,j}$ = available processing time for workstation i at time bucket j.

Step 3. Compute $s_i^{(k,l)}$

Contrast with step 2, the notation $\bar{d}_i^{(k)}$ is defined as follows:

$$\bar{d}_i^{(k)} = \sqrt{\sum_{j=1}^{m} w_{i,j}\left[\max\left(p_{i,j}^{(k)}, p_{i,j}^{(l)}\right)\right]^2}; \; i = 1, 2, \ldots, c \tag{4}$$

for the application of making up the mixed production batch, or

$$\bar{d}_i^{(k)} = \sqrt{\sum_{j=1}^{m} w_{i,j}\left(p_{i,j}^{(k)}\right)^2}; \; i = 1, 2, \ldots, c \tag{5}$$

for the application of capacity exchange, and obviously $\bar{d}_i^{(k)} \geq d_i^{(k,l)}$ for all l. In either case, $d_i^{(k,l)} = 0$; $i = 1, 2, \ldots, c$ clearly implies that the workload of product k can optimally match that of product l in workstation i, whereas the worst case is incurred when $d_i^{(k,l)} = \bar{d}_i^{(k)}$; $i = 1, 2, \ldots, c$.

Therefore, the similarity score for products k and l at workstation i can be calculated as follows:

$$s_i^{(k,l)} = \left(1 - \frac{d_i^{(k.l)}}{\bar{d}_i^{(k)}}\right) \times 100\%; \; i = 1, 2, \ldots, c. \tag{6}$$

Step 4. Calculate $s^{(k,l)}$

In this step, the similarity score between products k and l at every workstation is weighted by the relative utilization of workstations, and then summed for all workstations to obtain the degree of similarity.

$$s^{(k,l)} = \sum_{i=1}^{c} w_i s_i^{(k,l)}; \tag{7}$$

where,

$$w_i = \frac{\bar{\rho}_i}{\sum_{n=1}^{c} \bar{\rho}_n},$$

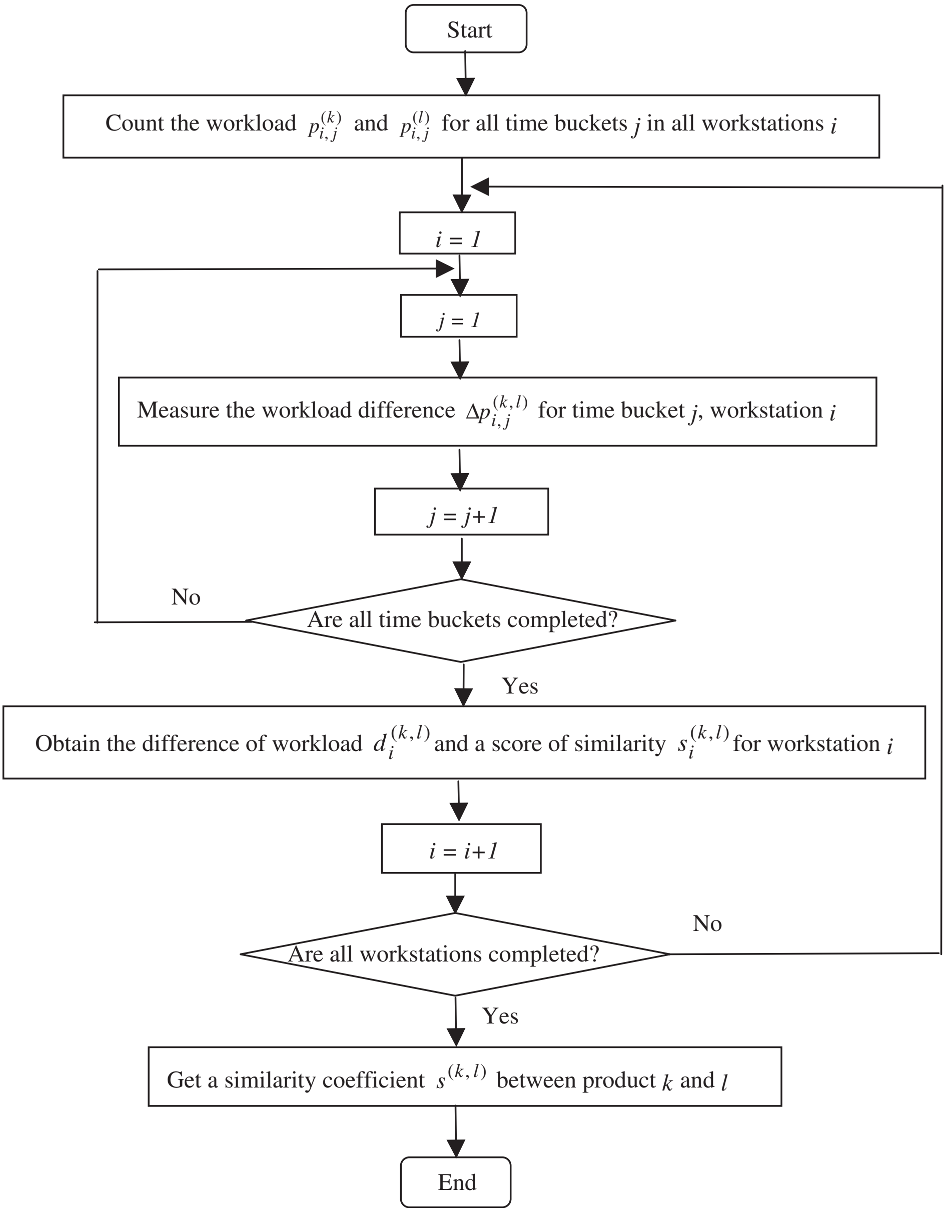

Figure 1. The flow chart of the similarity algorithm.

$\bar{\rho}_i$ = average utilization for workstation

$$i = \frac{\sum_{j=1}^{m} \rho_{i,j}}{m}.$$

Figure 1 illustrates the flow chart of the algorithm.

3. Numerical example

This section presents an example of capacity exchange, using data from a Taiwanese semiconductor manufacturer, to illustrate the usefulness of the proposed algorithm. The underlying manufacturing system in this example comprised the following features.

(1) The existing schedule comprised three prescheduled orders, PO1, PO2, PO3, involving 300 lots of product Log25, 500 lots of product Log35, and 500 lots of product Dram25, respectively.
(2) A new rush order, NO, was received, involving 600 lots of product Log18. Fulfilling this order on time would require exchanging production capacity with another order.
(3) Log18, Log25, Log35, and Dram25 require 386, 399, 369 and 407 manufacturing steps in their manufacturing processes, respectively.
(4) The manufacturing system contained a total of 78 types of workstation.
(5) The length of each time bucket was assumed to be 12 hours, and thus was divided into 40 time buckets for the duration of a planning horizon of 20 days.

Using the proposed algorithm, the three prescheduled orders would individually be compared with the new rush order from the perspective of manufacturing process to identify the degree of similarity between them. Due to space considerations, detailed production data, such as product manufacturing processes, processing times, current schedule information, and so on are ignored. For the same reasons, this study also omitted the workload $p_{i,j}^{(k)}$; $k = \text{Log18, Log25, Log35, Dram25}$ and workload differences $\Delta p_{i,j}^{(Log18,\, l)}$; $l = \text{Log25, Log35, Dram25}$ for the four products, and the load rate $\rho_{i,j}$ and weight $w_{i,j}$ at each time bucket j in every workstation i.

Table 1 lists the workload differences $d_i^{(Log18,\, l)}$; $l = \text{Log25, Log35, Dram25}$ and similarity scores $s_i^{(Log18,\, l)}$; $l = \text{Log25, Log35, Dram25}$ in all 78 types of workstations between the rush order product Log18 and the prescheduled order products Log25, Log35 and Dram25. Additionally, table 2 shows the equipment, average utilization $\bar{\rho}_i$ and weight w_i in all 78 types of workstations. Based on this data, table 3 shows the final similarity coefficients $s^{(Log\ \ 18,l)}$; $l = \text{Log25, Log35, Dram25}$ between rush order product Log18 and prescheduled order products Log25, Log35 and Dram25. From the outcome, it is clear that NO could be inserted at the expense of PO1 and PO3 (or part of PO3), because the quantity of accumulated lots from two prescheduled orders, namely 800, exceeds the quantity of 600 required by rush order.

4. Concluding remarks

This study developed a practical and reasonably simple algorithm for evaluating the degree of the manufacturing process similarities among various products. The algorithm can be applied to create mixed production batches that are widely used in several product-mix manufacturing environments, including product-oriented repetitive manufacturing, cellular manufacturing, and process-oriented manufacturing. The proposed algorithm also can be applied to optimize

Workstation (i)	PO1 vs. NO $d_i^{(Log18,Log25)}$	PO1 vs. NO $s_i^{(Log18,Log25)}$ (%)	PO2 vs. NO $d_i^{(Log18,Log35)}$	PO2 vs. NO $s_i^{(Log18,Log35)}$ (%)	PO3. NO $d_i^{(Log18,Dram25)}$	PO3. NO $s_i^{(Log18,Dram25)}$ (%)
DIFF1	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF2	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF3	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF4	0.00000	100.000	0.08671	69.849	0.00000	100.000
DIFF5	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF6	0.04022	96.983	0.00000	100.000	0.98769	47.615
DIFF7	0.00906	97.447	0.80582	37.032	0.00000	100.000
DIFF8	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF9	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF10	0.03919	98.367	3.06989	36.057	1.58743	58.111
DIFF11	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF12	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF13	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF14	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF15	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF16	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF17	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF18	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF19	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF20	0.00000	100.000	0.00000	100.000	0.00000	100.000
DIFF21	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH1	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH2-1	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH2-2	0.32963	57.992	0.18221	80.000	0.00000	100.000
ETCH3	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH4	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH5	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH6-1	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH6-2	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH7-1	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH7-2	0.00000	100.000	0.14965	91.792	0.00000	100.000
ETCH8-1	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH8-2	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH9-1	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH9-2	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH9-3	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH10	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH11	0.00000	100.000	0.39751	55.279	0.00000	100.000
ETCH12	0.00000	100.000	0.94638	55.279	0.60678	66.637
ETCH13-1	0.00000	100.000	0.20923	74.180	0.30155	69.539
ETCH13-2	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH14	0.00000	100.000	0.00000	100.000	0.00000	100.000
ETCH15	0.00000	100.000	0.00000	100.000	0.00000	100.000
PH1	0.00000	100.000	0.08862	60.777	0.12829	59.175
PH2	0.04737	88.371	0.23880	58.980	0.15102	78.249
PH3	0.14571	64.645	0.19843	65.794	0.11403	79.275
PH4-1	0.00000	100.000	0.00000	100.000	0.36257	74.480
PH4-2	0.00000	100.000	0.57865	56.329	0.30738	84.209
PH6	0.00000	100.000	0.00000	100.000	0.00000	100.000
PH7	0.00000	100.000	0.18837	60.777	0.21887	57.992
TF1	0.00000	100.000	0.00000	100.000	0.00000	100.000

Table 1. The workload differences and similarity scores of the products between rush order and prescheduled orders.

Workstation (i)	PO1 vs. NO $d_i^{(Log18,Log25)}$	$s_i^{(Log18,Log25)}$ (%)	PO2 vs. NO $d_i^{(Log18,Log35)}$	$s_i^{(Log18,Log35)}$ (%)	PO3. NO $d_i^{(Log18,Dram25)}$	$s_i^{(Log18,Dram25)}$ (%)
TF2	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF3	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF4	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF5	0.16659	79.982	0.00000	100.000	0.00000	100.000
TF6-1	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF6-2	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF7-1	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF7-2	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF7-3	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF8	0.00000	100.000	1.05475	55.005	0.00000	100.000
TF9	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF10-1	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF10-2	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF11	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF12-1	0.00000	100.000	0.23070	75.000	0.00000	100.000
TF12-2	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF12-3	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF13	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF14-1	0.06072	76.750	0.24787	47.295	0.00000	100.000
TF14-2	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF15	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF16	0.00000	100.000	0.00000	100.000	0.00000	100.000
TF17	0.24462	68.140	0.52318	63.591	0.85715	39.318
TF18	0.00000	100.000	0.07418	50.000	0.00000	100.000
WE1	0.00000	100.000	0.00000	100.000	0.00000	100.000
WE2	0.00000	100.000	0.00000	100.000	0.00000	100.000
WE3	0.00000	100.000	0.00000	100.000	0.00000	100.000

Table 1. Continued.

decisions on capacity exchange between rush orders and prescheduled orders, a growing practice in manufacturing in response to increasingly varied customer requirements and market demand, on better performance.

Notably, although various methods of evaluating manufacturing process similarity have been proposed in the literature, the proposed algorithm differs from these methods because it considers a dynamic bucketed production environment. That is, the proposed algorithm also takes account of such real time and dynamic production factors as load projection and workstation utilization in terms of the current detailed schedule. As a result, the proposed algorithm can be expected to indicate, more accurately, manufacturing process similarities among products. This expectation is supported by the rational and anticipative similarity outcomes of the numerical instance obtained for the semiconductor foundry used as an example in section 3. It can thus be seen that the similarity of manufacturing processes defined and developed should be able to serve as an accurate and reliable basis for helping to optimize certain tasks of the operation (execution) layer. These tasks, such as managing capacity exchange for a rush order under full capacity utilization and creating mixed production batches within a given job shop, are considered as subjects for future works.

Workstation	The number of equipment	Maximal lots/ machining	Utilization	Weight
DIFF1	2	6	0.9470	0.01840
DIFF2	2	6	0.9398	0.01826
DIFF3	5	6	0.9278	0.01802
DIFF4	4	1	0.5343	0.01039
DIFF5	14	6	0.9962	0.01935
DIFF6	5	1	0.4094	0.00795
DIFF7	7	1	0.5764	0.01120
DIFF8	2	4	0.9393	0.01825
DIFF9	1	1	0.2276	0.00442
DIFF10	8	2	0.7997	0.01553
DIFF11	4	6	0.8818	0.01713
DIFF12	2	2	0.7336	0.01425
DIFF13	2	2	0.8302	0.01613
DIFF14	7	6	0.9863	0.01916
DIFF15	2	2	0.5995	0.01165
DIFF16	1	2	0.7002	0.01360
DIFF17	6	6	0.9806	0.01905
DIFF18	3	6	0.9403	0.01826
DIFF19	7	6	0.9454	0.01836
DIFF20	2	4	0.6519	0.01266
DIFF21	5	5	0.8975	0.01743
ETCH1	1	1	0.1336	0.00260
ETCH2-1	2	2	0.5828	0.01132
ETCH2-2	5	2	0.9086	0.01765
ETCH3	4	1	0.5211	0.01012
ETCH4	2	1	0.7801	0.01515
ETCH5	11	1	0.7047	0.01369
ETCH6-1	4	1	0.6746	0.01310
ETCH6-2	4	1	0.7827	0.01520
ETCH7-1	6	1	0.7390	0.01435
ETCH7-2	13	1	0.6665	0.01295
ETCH8-1	3	1	0.6429	0.01249
ETCH8-2	2	1	0.4337	0.00842
ETCH9-1	2	1	0.7605	0.01477
ETCH9-2	2	1	0.6613	0.01285
ETCH9-3	2	1	0.3739	0.00726
ETCH10	1	2	0.7870	0.01529
ETCH11	4	2	0.8669	0.01684
ETCH12	7	2	0.9405	0.01827
ETCH13-1	12	1	0.7382	0.01434
ETCH13-2	1	1	0.1283	0.00249
ETCH14	11	1	0.8038	0.01561
ETCH15	2	1	0.6805	0.01322
PH1	5	1	0.5799	0.01126
PH2	11	1	0.6937	0.01347
PH3	11	1	0.6891	0.01339
PH4-1	13	1	0.6325	0.01229
PH4-2	17	1	0.7313	0.01421
PH6	4	1	0.5953	0.01156
PH7	6	1	0.7546	0.01466
TF1	5	1	0.6220	0.01208
TF2	9	1	0.7308	0.01420
TF3	7	1	0.6444	0.01252

Table 2. The equipment and utilization for all types of workstation.

Workstation	The number of equipment	Maximal lots/ machining	Utilization	Weight
TF4	2	1	0.2923	0.00568
TF5	5	1	0.6137	0.01192
TF6-1	7	1	0.6688	0.01299
TF6-2	2	1	0.4604	0.00894
TF7-1	3	1	0.6140	0.01193
TF7-2	6	1	0.6133	0.01191
TF7-3	5	1	0.6384	0.01240
TF8	12	1	0.6530	0.01268
TF9	7	1	0.5431	0.01055
TF10-1	3	1	0.5445	0.01058
TF10-2	6	1	0.7360	0.01430
TF11	2	1	0.5146	0.01000
TF12-1	10	1	0.7530	0.01463
TF12-2	3	1	0.6670	0.01296
TF12-3	3	1	0.6582	0.01279
TF13	3	1	0.5624	0.01092
TF14-1	3	1	0.7785	0.01512
TF14-2	3	1	0.3520	0.00684
TF15	6	1	0.7310	0.01420
TF16	2	1	0.2630	0.00511
TF17	14	1	0.6824	0.01326
TF18	5	1	0.0760	0.00148
WE1	4	1	0.5947	0.01155
WE2	5	1	0.4831	0.00938
WE3	11	1	0.5595	0.01087

Table 2. Continued.

The prescheduled order (Product)	Similarity coefficient	The number of lot
PO1 (Log25)	$s^{(Log18,Log25)} = 0.98762$	300
PO3 (Dram25)	$s^{(Log18,Dram25)} = 0.97416$	500
PO2 (Log35)	$s^{(Log18,Log35)} = 0.95211$	500

Table 3. The similarity coefficients of products between rush order and prescheduled orders.

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