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A METHOD FOR OPTIMIZING THE RECONFIGURATION DESIGN TASK IN MANUFACTURING SYSTEMS

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Abstract

This paper discusses an innovative method for optimizing the reconfiguration design task in manufacturing systems. System–level reconfiguration is re-formulated as an optimization problem. The optimization framework is enhanced by employing: a structured matrix, a relationship matrix and simulation modeling. The objective function is obtained by simulating system characteristics through the combined support of a relationship matrix and a design variables vector. A case illustration of this method shows that an optimal design solution can be reached. However, the solution depends on the implemented reconfiguration policy and is influenced by relative weighting of system characteristics. Therefore, this method is suitable for optimizing the reconfiguration design task.

Keywords
Reconfiguration, structured matrix (SM), relationship matrix (RM), numerical simulation, optimization, reconfigurable manufacturing systems

1. Introduction
Reconfiguration of a manufacturing system entails the selection of a new configuration that meets current constraints or new desired needs in the operations of a manufacturing system [1]. In this paper, we focus on developing a method for the reconfiguration task in manufacturing systems that are designed to be reconfigurable.

A manufacturing system is said to be reconfigurable if its system components can be changed or tailored to respond to changes in production requirements [2, 3]. Reconfiguration can be done at any level of a manufacturing system including; device level, machine level and system or cell level [4]. The discussions in this paper focus on system level reconfiguration of manufacturing systems that operate under dynamic manufacturing environments.

Generally, dynamic manufacturing environments are characterized by continual changes in production requirements. In response, manufacturers often seek cost-effective methods of reconfiguring the manufacturing system in order to match the required changes. Usually, a decision to reconfigure has to be made based on many operational parameters and a number of constrains have to be considered before a matching solution can be reached. This often requires a consensus input from a number of expert profiles. Therefore, the reconfiguration task can naturally be cast as a design problem.

At system level, reconfiguration is carried out to select/re-select a manufacturing system configuration that is optimally fit for current production requirements. For the sake of analysis, reconfiguration activities usually take various forms including: capacity reconfiguration, scheduling reconfiguration, functionality reconfiguration and conversion reconfiguration [5]. Due to a large amount of information to be processed prior to reconfiguration, a number of feasible solutions are often possible. Complex relationships also exist among the various system parameters. Albeit, the selected system configuration must be optimally fit for current purpose in addition to being cost effective, efficient and robust for a specific planning horizon. However, the objectives of the various criteria may conflict and, often, trade-offs may be deemed necessary depending on circumstances [6]. In light of the above discussion, the reconfiguration design task must be reformulated as an optimization problem. This approach ensures that a sub-optimal system solution will not be implemented.

From a systems design perspective, the focus in system-level reconfiguration is not on the detailed design of individual system components (i.e. machines, modules or devices) but on the interrelationships of system components. Consequently, a lot of design attributes and large information flows will characterize the reconfiguration design task. To enhance the design process, we proposed an innovative method that is based on re-formulating the conventional design problem into an optimization problem that takes into consideration subjective judgments of expert profiles. The optimization framework is essentially a structured approach that is supported by the following tools: a structured matrix (SM), a relationship matrix (RM), and simulation modeling, in the optimization procedure. Development of the SM tool derives inspiration from the *design structure matrix* technique [7] and is employed to document, visualize and keep track of production information flows during the reconfiguration design process. Development of the RM tool derives inspiration from the extended *quality function deployment* (QFD) methodology [8-10] and is employed to determine how specific attributes affect system characteristics.

In light of the previous discussions, the objective of this work is to develop a multi-objective optimization method for the system-level reconfiguration design task in manufacturing systems. In pursuing this work we try to answer the following questions: (i) how do we formulate/reformulate the reconfiguration design task as an optimization problem? (ii) how do we support the formulation of the objective function in order to advance the optimization of the reconfiguration design task?

2. Reconfiguration design task

In any optimization problem, a number of systems characteristics have to be considered. In most cases, trade-off techniques are employed in order to arrive at an optimal solution. In conventional optimization processes, the objective function value corresponds to the value of a particular design attribute. The multi-objective design problem can then be formulated by assigning values to system parameters that ensure that the design attributes are satisfied for a range of operating variables. A general multi-objective conventional design problem can be expressed by the equation by the following equation [11]:

$$Min\ F(y) = [f_1(y), f_2(y), ...f_l(y)],\ \text{s.t. } y \in S,\ y = (y_1, y_2, ...y_m)^T \tag{1}$$

In Equation (1): $f_1(y), f_2(y), ..., f_l(y)$ are the l objective functions; $(x_1, x_2, ...x_m)$ are the m optimization parameters, and $S \in R^m$ is the solution or parameter space. Obtainable objective vectors, $\{F(y) | y \in S\}$, are denoted by Y, so that S is mapped by **F** onto Y. $Y \in R^l$ is the attribute or criteria space, where ∂Y is the boundary of Y. Generally F is usually non-linear and S maybe be defined by non-linear constraints and may contain both continuous and discrete member variables. If $f_1^*, f_2^*, ...f_k^*$ denotes the individual minima of the corresponding objective function, then the utopian solution is defined as:

$$F^* = (f_1^*, f_2^*, ...f_k^*) \tag{2}$$

Since F^*, in Equation (2) minimizes all objectives simultaneously, it is an ideal solution. However, *Min F(y)* in equation (1) is ambiguous since the set *{F(y)}* for all *y* is not ordered whenever *F(y)* is vector-valued. Therefore, subjective judgment from the decision maker is required in order to determine whether $F(y_1)$ is better than $F(y_2)$. In practice, a number of expert profiles are usually consulted for reconfiguration decisions. In the proposed method, it is the input from such expert profiles that plays the role of ordering the solution set, *{F(y)}*.

The general design problem discussed above is reformulated as an optimization problem by introducing supporting information, which is deployed through tools such as the SM and the RM. In the optimization procedure, the SM is used to choose relevant optimization parameters, while the RM supports the formulation of the objective function. Data to be represented in the SM is derived from system-level functions since we want to represent system component relationships for system configuration. These innovative concepts are used to cast the conventional design problem as a multi variable constrained optimization problem [12]. The problem is to minimize the function:

$$F(y_1, y_2, ...y_m) \qquad\qquad y \in S \tag{3}$$

In essence, the objective function must reflect all relevant system characteristics determined from the RM developed for a specific manufacturing system. Each of the relevant system characteristics is expressed as a function of the optimization parameters $f_i = f_i(y_1, y_2, ...y_m)$. If the objective function is to minimize the system characteristics i.e.

$f_1, f_2, ... f_i$, then the objective function F can be represented as:

$$F = \left(\frac{f_1}{f_n}\right)^{\delta_1} + \left(\frac{f_2}{f_{n2}}\right)^{\delta_2} + ... + \left(\frac{f_j}{f_{j0}}\right)^{\delta_j} \tag{4}$$

where $f_n, f_{n2}, ... f_{j0}$ are the function values from an evaluation of one initial acceptable system, e.g. $f_{j0} = f_j(y_n, y_{n2, ...} y_{j0})$, for which $y_{i0, ...} y_{n0,}$ are the parameters of the initial solution. The indices $\delta_i ... \delta_j$ represent the relative importance of the different objective functions and can be expressed as functions of the weighting factors from the relationship matrix (RM). The functions $f_1, f_2, ... f_i$, normalize the different characteristics and reduce the problem to finding one acceptable solution that the optimization strategy tries to improve. In order to handle design constraints, a constant polynomial is multiplied with the original objective function. The objective function can then be written as:

$$F = \underbrace{\left[\left(\frac{f_1}{f_n}\right)^{\delta i} + \left(\frac{f_2}{f_{n2}}\right)^{\delta_2} + ... + \left(\frac{f_j}{f_{j0}}\right)^{\delta j}\right]}_{\textbf{\textit{problem objectives}}} \textbf{ x } \underbrace{\left((1 + c_1)^{\lambda_1} + (1 + c_2)^{\gamma_2} + ... + (1 + c_j)^{\lambda_j}\right)}_{\textbf{\textit{problem constraints}}} \tag{5}$$

where, c_j, is a function that equals zero if the j^{th} constraint is not violated and significantly greater than unity otherwise λ_j indicates the strength of the j^{th} constraint.

3. Multi-Objective Optimization Approach

The proposed design optimization strategy is shown in Figure 1. The proposal is to first generate an SM in order to capture system configuration optimization coefficients. The SM represents configuration constraints that may not be violated in the design process. However, trade-offs may be deemed necessary thus justifying constraint relaxation as defined by the SM.

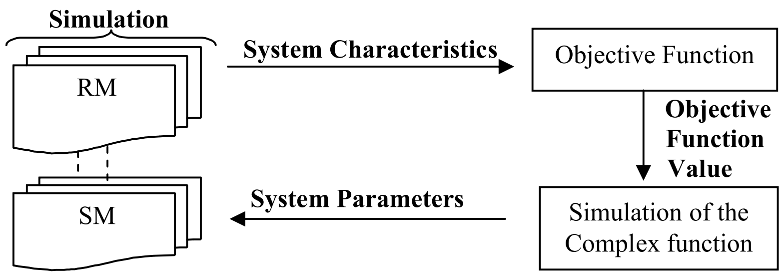

Figure 1: Optimization strategy for the reconfiguration design task

The next step is to derive an RM from which pertinent characteristics needed for the formulation of the objective function can be identified. Through numerical simulations based on an optimized RM, the design variable vectors are generated and thus specify optimal system parameters. The technique for developing the SM is based on the concept of similarity coefficients that takes into account relevant production information such as: process routings, process sequence and volumes of parts transported between processing units [13]. The SM is derived from the similarity coefficient equations. The processing unit chain similarity coefficient *(puCS)* between processing elements *i* and *j* is given by the equation:

$$puCS_{ij} = \begin{cases} \dfrac{\sum_{\beta=1}^{M}\left(\min\left(\sum_{k=1}^{N} P_{i\beta}^{k}, \sum_{k=1}^{N} P_{j\beta}^{k}\right)\right) if\ i \neq j}{\sum_{\beta=1}^{M}\sum_{k=1}^{N}\left(V_{k\beta} + V'_{k\beta}\right) if\ i = j} \\ 1 \end{cases} \tag{6}$$

where $V_{k\beta}$ = volume of k^{th} part moved out from processing element β, $V_{k\beta}'$ is the volume of the k^{th} part moved in to processing element β, N, is the number of parts, M is the number of processing elements, and:

$$P_{i\beta}^{k} = \begin{cases} \sum_{k=1}^{N} \sum_{i=1}^{G_k} C_1 V_k & \text{if } i = 1 \\ \sum_{k=1}^{N} \sum_{i=I}^{G_k} W_{i\beta}^{k} V_k & \text{if } i \neq 1 \end{cases} \tag{7}$$

where $C_l = \begin{cases} 1 & \text{if } (\beta = 1 \text{ or } \beta = G_k) \\ 2 & \text{otherwise} \end{cases}$, G_k, is the last processing element in the route of part type k, V_k, is the production volume for part type k and $W_{i\beta}^{k}$, is the number of trips that part type k makes between processing elements i and β.

The technique for developing the RM is based on an extension of the QFD method (cast as the relationships between the HOWs and WHATs in building the house of quality) and is similar to finding a vector of the design variables represented mathematically as:

$$\text{Find } v = [D, \ \ where \ \ V == (HOWs)] \text{ that minimizes the function } F(v) \text{ for which :}$$

$$(F(v))_p = [WH]^T (ww)_p \tag{8}$$

where i = 1, 2, 3,….,n; j = 1, 2, 3,…., m, and p is the column index of the HOWs versus WHATs (*HW*) relation matrix and it represents the weighting factors associated with WHATs. In Equation (8), *WH* is a sensitivity matrix defined by the WHATs versus HOWs and *ww* is a list vector belonging to the influence matrix defined by the WHATs versus WHYs in the QFD process [10]. Continuing with the analogy to building the house of quality, the list of WHATs represents a series of objective functions (reconfiguration requirements), the list of HOWs represents an array of design variables through which the WHATs can be realized and WHYs is a list vector that represents the relative importance of the reconfiguration requirements.

As discussed earlier on, the aim of the reconfiguration design task is to select an optimal arrangement of resources for processing tasks at minimum cost. The selected processing units (machines and equipment) for each manufacturing station has a strong influence on the processing costs, production volumes transported between the processing units and hence affect the effectiveness of the configuration. In the conventional approach, the general objective function for a reconfigurable manufacturing system can then be expressed as follows:

$$\min \ \ F(x) = Cost / Throughput \tag{9}$$

Equation (9) the numerator, cost is a function that can be used to estimate total costs incurred during reconfiguration and is composed of: reconfiguration cost (*RC*), ramp-up cost (*RampC*), operation (*OC*) and support cost (*SC*). The denominator, throughput function, is used to estimate the throughput of a part, P_i, in the configuration of an array of processing units/machines, *PU*[ ] that make-up the system for: a specified machine reliability matrix, *R*[ ], a specified task allocation matrix, X[ ], and a specified size of the productive reserve capacity, $K_{[s]}$ [ ]. Substituting these values, Equation (9) can be rewritten as follows:

$$\min \ \ F(x) = \frac{\sum_{i=1}^{a} k_1 * RC + \sum_{i=1}^{a} k_2 * RampC + \sum_{i=1}^{a} k_3 * OC + \sum_{i=1}^{a} k_4 * SC}{\sum_{i=1}^{P} (p, PU[], R[], X[], K[s])} \tag{10}$$

subject to the following constraints: processing sequence, task precedence, functionality, capacity and routing flexibility. The formulation in Equation (10) contains implicit complex functions that cannot be directly evaluated. Usually, heuristic algorithms are employed to handle this implicit function. To enhance the analytical process, the formulation of the objective function implemented in this paper is simplified by developing a RM through the extension of the QFD concept and its application to optimizing engineering resources [8, 9]

The QFD is extended to an operating requirements matrix that examines the changes needed in operating practices to support reconfiguration requirements in the system. Such an extension provides a better understanding of reconfiguration parameters and their influence on the technical elements of the reconfiguration design task and hence allow priorities to be defined for the reconfiguration effort. The RM is optimized through application of Equation (8). The implicit function in Equation (10) is captured in both the SM and the RM tools in the development of the optimization strategy proposed in this paper. The proposed optimization strategy is illustrated in the following section.

4. Case Illustration

The case illustration considers 20 different part types which are processed by 14 processing units (machines and equipment) that make up a modular manufacturing line. Task precedence and throughput demands are aggregated in the relevant production data for the 20 parts shown in Table 1. Part routes (route) are identified by the processing units (machine numbers) that parts (P_i) visit to complete production in the production line. Processing elements (PEs) are specific processing elements in the production line and the production volumes (PV) are also shown.

Table 1: Relevant production information for the case study

P i	*1*	*2*	*3*	*4*	*5*
PV	10000	9000	12000	12000	12000
route	1 1-2 1-2 5-3 1-3 2-4 1-4 2	1 2-2 7-3 3-42	1 1-2 4-2 8-2 9-2 10-2 11-3 3-4 1-4 2	1 2-2 2-2 3-2 6-3 3-4 2	1 1-2 1-2 5-3 1-3 2-4 1-4 2
PEs	11;21;24;31;32;41;42	12;23;34;42	11;23;22;25;26;27;34;41;42	12;21;22;24;34;42	11;21;24;31;32;41;42
P i	*6*	*7*	*8*	*9*	*10*
PV	11000	9000	8000	7500	10000
route	1 2-2 2-2 3-2 6-3 2-4 2	1 2-2 1-2 5-3 1-3 2-4 1-4 2	1 1-2 2-2 4-2 8-2 10-2 11-3 3-4 2	1 2-2 1-2 5-2 9-3 1-3 2-4 2	1 1-2 4-2 8-2 9-2 10-2 11-3 3-4 2
PEs	12;21;22;24;32;42	12;21;24;31;32;41;42	11;21;23;22;26;27;34;42	12;21;24;25;31;32;42	11;23;22;25;26;27;34;42
P i	*11*	*12*	*13*	*14*	*15*
PV	9000	7000	7000	7000	10000
route	1 2-2 4-2 9-2 10-2 11-3 3-4 1-4 2	1 1-2 7-3 3-4 2	1 1-2 6-2 7-3 3-4 1-4 2	1 2-2 4-2 8-2 9-2 10-3 3-4 2	1 2-2 5-3 1-3 2-4 1-4 2
PEs	12;23;25;26;27;34;41;42	11;23;34;42	11;24;23;34;41;42	12;23;22;25;26;34;42	12;24;31;32;41;42
P i	*16*	*17*	*18*	*19*	*20*
PV	11000	7000	8000	8000	8000
route	1 1-2 2-2 3-2 6-3 2-4 1-4 2	1 2-2 4-2 8-2 9-2 10-2 11-3 3-4 2	1 2-2 1-2 5-3 1-3 2-4 1-4 2	1 2-2 1-2 5-3 1-3 2-4 1-4 2	1 1-2 2-2 3-2 6-3 2-4 1-4 2
PEs	11;21;22;24;32;41;42	12;23;22;25;26;27;34;42	12;21;24;31;32;41;42	12;21;24;31;32;41;42	11;21;22;24;32;41;42

Table 2 shows normalized values that represent volumes of parts transported between processing units as well as process sequences, which make up the major processing constraints. Values in Table 2 are calculated based on Equations (6) and (7).

Table 2: An example structured matrix (SM) showing the couplings between different processing units in the manufacturing system

Processing Elements in the MPL	Processing Elements in the MPL													
	1 1	**1 2**	**2 1**	**2 2**	**2 3**	**2 4**	**2 5**	**2 6**	**2 7**	**3 1**	**3 2**	**3 4**	**4 1**	**4 2**
1 1	**1.0000**	0.3869	0.4328	0.3886	0.2866	0.3881	0.2635	0.2509	0.2412	0.2330	0.3520	0.3207	0.4377	0.5229
1 2	0.0000	**1.0000**	0.4080	0.3731	0.2692	0.4015	0.2578	0.2132	0.2164	0.2838	0.3626	0.3041	0.4503	0.5193
2 1	0.4328	0.4080	**1.0000**	0.3398	0.2221	0.5534	0.1985	0.1790	0.1636	0.2680	0.4332	0.2732	0.5039	0.6033
2 2	0.3886	0.3731	0.3398	**1.0000**	0.3337	0.3187	0.2952	0.2883	0.2607	0.2152	0.2879	0.3362	0.3792	0.4742
2 3	0.2866	0.2692	0.2221	0.3337	**1.0000**	0.2075	0.3447	0.3402	0.3021	0.1218	0.1766	0.4206	0.2745	0.4206
2 4	0.3881	0.4015	0.5534	0.3187	0.2075	**1.0000**	0.1839	0.1644	0.2038	0.3285	0.4490	0.2521	0.4933	0.6127
2 5	0.2635	0.2578	0.1985	0.2952	0.3447	0.1839	**1.0000**	0.3069	0.2862	0.1425	0.1579	0.3216	0.2493	0.3398
2 6	0.2509	0.2132	0.1790	0.2883	0.3402	0.1644	0.3069	**1.0000**	0.3021	0.1031	0.1401	0.3402	0.2314	0.3402
2 7	0.2412	0.2164	0.1636	0.2607	0.3021	0.2038	0.2862	0.3021	**1.0000**	0.0974	0.1279	0.3021	0.2184	0.3021
3 1	0.2330	0.2838	0.2680	0.2152	0.1218	0.3285	0.1425	0.1031	0.0974	**1.0000**	0.3285	0.1498	0.3078	0.3130
3 2	0.3520	0.3626	0.4332	0.2879	0.1766	0.4490	0.1579	0.1401	0.1279	0.3285	**1.0000**	0.2213	0.4584	0.5108
3 4	0.3207	0.3041	0.2732	0.3362	0.4206	0.2521	0.3216	0.3402	0.3021	0.1498	0.2213	**1.0000**	0.3126	0.4799
4 1	0.4377	0.4503	0.5039	0.3792	0.2745	0.4933	0.2493	0.2314	0.2184	0.3078	0.4584	0.3126	**1.0000**	0.5830
4 2	0.5229	0.5193	0.6033	0.4742	0.4206	0.6127	0.3398	0.3402	0.3021	0.3130	0.5108	0.4799	0.5830	**1.0000**

In essence, Table 2 is a structured matrix (SM) that shows normalized optimization coefficients for pairwise couplings between different processing units/machines in the manufacturing system. It captures and visualizes system level configuration constraints that must be satisfied to facilitate cost-effective movement of parts to and from and between the processing units in the manufacturing system. Any configuration chosen should, under normal circumstances, comply and satisfy the sequence links indicated in the SM. However, relaxation may be allowed in trade-off treatments. The optimization problem was formulated based on the following reconfiguration metrics or system characteristics: scalability, convertibility, quality, productivity, customizability, integrability, modularity and diagnosibility [1, 2]. The formulation of the implemented objective function is similar to that described in Equations (1)-(5). Table 3 shows the relationship matrix (RM) that expresses the relationships between system reconfiguration characteristics and the critical system reconfiguration parameters.

In Table 3, a weak dependency indicates that a requirement does not necessarily have to be included in the objective function. Therefore, the RM provides data that can be used in deciding which requirements should be taken into account in the formulation of the objective function. The RM is derived according to Equation (8). In Table 3; *flows* represents the number of alternative flows for parts, α is a factor for materials handling to the productive reserve capacity, β is the factor for production efficiency in the reserve capacity, μ_m is the production rate, $min.\partial V$ is the minimum capacity increment, $\Delta\mu$, is the mean deviation, σ, is the standard deviation, R represents system reliability, m stands for the number of parallel lines in the current configuration of the manufacturing system, n stands for the number of processing stages in the current manufacturing systems, k/l represents is the productive reserve capacity [14], while $cost/\partial V$ is the minimum cost increment for a given manufacturing configuration.

Table 3: An example normalized relationship matrix (RM) for the case manufacturing system

		1	system parameters											
		rel.weit.	***R***	***m***	***n***	***flows***	**α**	**β**	***k/l***	**μ_m**	***min.∂V***	**$\Delta\mu$**	**σ**	***cost/∂V***
system characteristics	scalability	**0.25**	0.20	0.20	0.20	0.20	0.00	0.00	0.60	0.60	1.00	0.00	0.00	1.00
	convertibility	**0.25**	0.20	0.40	0.40	1.00	0.20	0.20	0.60	0.00	1.00	0.00	0.00	0.20
	quality	**0.25**	0.00	0.20	0.20	1.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	0.00
	productivity	**0.25**	1.00	0.60	0.80	0.40	0.40	0.80	0.80	1.00	0.00	0.00	0.00	0.00
	customizability		0.00	0.00	0.00	0.00	0.20	0.20	0.20	0.00	0.00	0.00	0.00	0.00
	diagnosibility		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	integrability		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	modularity		0.00	0.00	0.20	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

In Table 3, the dependencies of the characteristics customizability, diagnosibility, integrability and modularity are weak. This is not surprising since these characteristics are often inherently satisfied in the physical manufacturing system design since the manufacturing system under study is considered to be reconfigurable. Therefore, from Table 3, the formulation of the objective function can consider scalability, convertibility, quality and productivity as the pertinent system characteristics since they have significant relationships with the system parameters. The system characteristics are given a weighting that indicates their relative importance. The relative weights in Table 3 are assumed to contribute equally. In practice, subjective judgements on system characteristics from expert profiles may differ. In such a case, the design variables vector values may change significantly. An example of the design variable vector for the manufacturing system under study is shown in Table 4 and is derived according to Equation (8).

Table 4: Design Variables Vector for Equal Weightings

					design variables vector											
[WH]^T				**[WW]**	*R*	*m*	*n*	*flows*	α	β	*k/l*	μ_m	*min.∂V*	$\Delta\mu$	σ	*cost/∂V*
0.2	0.2	0	1	0.25	**0.35**	**0.25**	**0.40**	**0.65**	**0.15**	**0.25**	**0.50**	**0.40**	**0.50**	**0.25**	**0.25**	**0.30**
0.2	0.4	0.2	0.6	0.25												
0.2	0.4	0.2	0.8	0.25												
0.2	1	1	0.4	0.25												
0	0.2	0	0.4													
0	0.2	0	0.8													
0.6	0.6	0	0.8													
0.6	0	0	1													
1	1	0	0													
0	0	1	0													
0	0	1	0													
1	0.2	0	0													

In the numerical simulation procedure for the design vectors, the weights are varied according to an interval reference technique (which consideres experts opinions through a weighting system) which is derived from a reconfiguration policy for operating the manufacturing system. The reconfiguration policy is used by decision makers to determine the appropriate vector to be used for the design variables. In the reconfiguration policy, each of the system characteristics can be used as a reference for calculating the relative weighting. Thus, a matrix of design vectors is generated, through numerical simulation. An example of a simulated matrix of design vectors derived from the RM in Table 3 is presented in Table 5.

Table 5: Priority vectors of system design variables

system design objectives													
vectors	**R**	**m**	**n**	**flows**	**α**	**β**	**k/l**	**μm**	**min.∂V**	**Δμ**	**σ**	**cost/∂V**	**reconfiguration policy**
1	0.23	0.16	0.26	0.42	0.10	0.16	0.33	0.26	0.33	0.16	0.16	0.20	*equal weightings*
2	0.74	0.48	0.70	0.74	0.30	0.57	0.78	0.78	0.43	0.22	0.22	0.26	*pV as reference*
3	0.30	0.30	0.43	1.00	0.13	0.22	0.43	0.35	0.43	0.65	0.65	0.26	*qV as reference*
4	0.39	0.22	0.52	1.00	0.22	0.30	0.69	0.35	0.87	0.22	0.22	0.35	*cV as reference*
5	0.39	0.30	0.43	0.65	0.13	0.22	0.69	0.61	0.87	0.22	0.22	0.70	*sV as reference*

The reference attributes, as defined in the reconfiguration policy, are also indicated as follows: *pV*-productivity as reference, *qV*-quality as reference, *cV*-convertibility as reference and *sV*-scalability as reference. Table 5 shows five design vectors each with specific system parameters that indicate the direction or path for reconfiguration activities (in terms of a normalized weight according to their relative importance). These design vectors are then considered as design variables in the optimization procedure. Since all vectors in Table 5 are feasible solutions, an optimal solution can then be selected based on reconfiguration policy chosen for the current state of production requirements. For example, if the changes in production requirements are mainly to do with changes in production volumes then the optimal solution is defined by vector 2, otherwise if changes are maily to do with quality of the manufactured product then the optimal solution is defined by vector 3 in Table 5.

5. Concluding Remarks

A method for reformulating the system–level reconfiguration design task as a multi-objective optimization problem has been outlined. The method utilizes a structured matrix, a relationship matrix, and numerical simulation to handle optimization of an implicit objective function. The structured matrix was employed to visualize and keep track of production information during the design process. This was done through a vector matrix that indicates constraint satisfaction in system configuration arrangements. The advantage of this approach is that it is simple to use and is also self documenting. The relationship matrix was used to determine how specific system parameters affect manufacturing system characteristics and was used to derive design variables vector. The objective function was optimized by simulating system characteristics through the support of the relationship matrix and the design variables vector. The results indicate that the optimal solution depends on the implemented reconfiguration policy and is influenced by the relative weightings of the system characteristics that define reconfigurability of the manufacturing system. The flexibility in the inclusion of the preferential weighting from a number of expert profiles in system characteristics during the optimization procedure means that the proposed approach is capable of being tailored to any dominant production scenario as defined by the required changes in production. Such an approach is, therefore, suitable for manufacturing systems that are designed to tailor changes in production requirements. Future work includes: (i) developing an algorithm to handle the reconfiguration design task and (ii) developing an expert system for optimizing the reconfiguration design task.

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