



An integrated approach for the configuration of automated manufacturing systems

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Abstract

The paper proposes a new integrated approach for supporting firms in their decisions of dimensioning automated production systems. The problem is closely related to the performance evaluation of the system since discriminating indicators are necessary to rank different alternatives. Traditionally, analytical methods and simulation have been used to evaluate the production system performance, with minor emphasis on the relationships between the tools and their use. Given the complexity of the problem, it is not possible to use only analytical methods that cannot enter deeply in problem details; at the same time the space of potential system configurations is too large to be evaluated by means of detailed tools such as simulation. In the proposed methodology, the problem is decomposed hierarchically into different sub-problems; each one has a different level of detail and a specific performance evaluation tool is used. At each level of the analysis, each system configuration is compared, by means of statistical tests, with the other alternatives with the purpose of discarding unprofitable solutions. © 2001 Elsevier Science Ltd. All rights reserved.

1. Introduction

Configuration of manufacturing systems is a strategic decision that many firms have to take every time they acquire a new system or modify an existing one. Regardless of the cause, firms have to solve the challenging problem of selecting the resources that fit their needs better. This is a very critical phase since each decision taken at this level will directly affect the performance of the new system and therefore its profitability over the following years. In addition, the information available is not detailed and is often uncertain. In particular, uncertainty of the market demand must be considered during the configuration of the production system since unexpected variations of the volumes required by the market, or the introduction of new products, can make the solution unsuitable to fulfil the market requests. At the same time, the decision must consider many system variables such as the number of machines, fixtures, carriers and tools and moreover dependencies among system variables are often unknown and are not easy to evaluate. To solve the problem, a methodology

that can deal with all the aspects described above is necessary.

The configuration of production systems is a problem that has been deeply investigated in the last years. An important line of research is devoted to stochastic models of flexible manufacturing systems (FMS). There are certain inherent factors that motivate the use of stochastic modelling for an FMS. An example is a machine breakdown which is an unforeseen disruption to the behaviour of the system; this is typically captured by a stochastic model. Other less important factors with a stochastic nature are load/unload (if not automated), tool breakdowns etc. The presence of the above factors, which require modelling the random components of an FMS, is only a partial justification for the use of stochastic modelling techniques. In fact, the key argument for the justification of a stochastic model seems to be the lack of exact information on the part mix to be produced on the system. Buzacott and Yao present a literature review of the analytical models of FMSs covering the works of different groups until the mid 1980s [1]. Solot and Van Vliet provide an updated account of the analytical modelling literature for FMS systems [2]. Solot and Van Vliet classify the analytical models according to the corresponding problems addressed. Five major classes are

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identified: processing capacity, buffer capacity, facility layout, pallet quantity and material handling system. It is recognised that the most frequently studied problem is that of optimising processing-capacity in terms of machine allocation and grouping [3,4].

Discrete event simulation tools enable a very detailed analysis of the underlying system to be analysed. For FMS systems, a discrete event simulation can almost mimic the dynamic behaviour of the actual system by explicitly modelling machine operations, pallet movement, part carrier, tool changing and operations, etc. This is a major advantage over an analytical model which is usually a crude approximation that ignores many important detailed features of the underlying system. On the other hand, the main drawback of a simulation model is that the output of a simulation run is the outcome of a statistical experiment since a simulation run generates one of the infinitely many possible realisations of the system's dynamic behaviour. Therefore, the outputs of simulation experiments have to be treated as statistical experiments, which imply running and analysing the results of a large number of experiments to obtain statistically reliable estimates of the performance measures.

An interesting approach is, then, using analytical methods for an initial selection of good configuration candidates and then refining the choice among the selected candidates by performing a few simulation experiments. This two-step approach benefits from the speed of analytical methods in the initial phase for eliminating distinctively poor configurations and in the second phase makes use of the detailed modelling feature of simulation to search for the best candidate; an application of the two-step approach is presented by Starr [5], Dekleva and Gaberc [6]. The authors present the implementation of the integrated analytical/simulation performance evaluation tool in a software. In this way, initial design iterations can be performed rapidly using the analytical module and the simulation module can provide refinements.

The paper is organised as follows. Section 2 contains a general view of the proposed method while Section 3 describes the technique in detail; the methodology is applied to a real case in Section 4 and conclusions are finally reported in Section 5.

2. The approach

The objective of the proposed method is to identify a set of alternative production systems among which the decision-maker, the manager of the firm, can select the one he considers the best. In order to facilitate the task, the set should be as limited as possible and some performance indicators should be provided. In such a method, the manager can compare different production systems of

the set on the basis of the performance indicators provided by the method.

Allocating the system resources is a challenging task due to different reasons. First of all the number of resources that have to be allocated in the configuration problem is high. The manager has to decide the number of machines, part carriers, fixtures, copies of tools, tool carriers, load/unload stations, etc., to purchase. It is not rare to find in shop floor systems with at least four machines working more than 15 different part types, each product with a set of dedicated fixtures, with more than 200 copies of tools in the system. The combination of all the resources that have to be allocated leads to an explosion of possible alternative production systems. Second, the interactions among resources are often unknown and are difficult to evaluate. For instance, it is not easy to estimate the effect that an increase or a decrease of the number of pallets can have on the saturation of machines. Third, the problem is stochastic in its nature because of the variability of market demand, machine failures, processing times, etc., and the solution must take this aspect into account.

Therefore, given the high complexity of the problem and the infeasibility of considering all the decision variables at the same time, we propose a hierarchical approach in which the problem is decomposed into different ones. In each sub-problem, the production system is represented with a specified level of detail that increases from the top of the hierarchy to the bottom. At higher levels, the system is modelled taking into account a limited number of decision variables, in particular, those that have a major impact on the system behaviour. On the other hand, at lower levels of the hierarchy, the system is represented in detail, taking into account other decision variables that are less important than those of the higher level; in particular, other decision variables are considered in addition to those already considered in the higher levels. For instance, the number of machines, which has a significant impact on the system behaviour, must be considered at higher levels while the number of copies of tools, which has a lesser impact in comparison with that of machines, can be included at lower levels. The complexity and the accuracy of the analysis increase from the higher levels to the lower levels.

Starting from the top of the hierarchy, the method works in different steps until the lowest level is reached. At each level l , there is a set of alternative production systems that must be compared on the basis of the indicator that the firm wants to maximise. To achieve this, it is necessary to have a tool that is able to evaluate, for each alternative, performance measures such as production rates, machine saturation, buffer levels, etc. Simulation is used when the desired detail level of the analysis is high; the computational effort of the tool is high but the tool provides accurate results. For instance, it is necessary to use simulation when we compare two

similar production systems that differ only in the number of copies of tools, since by simulation we can measure small differences in terms of performance between them. On the contrary, approximate analytical methods are used when the requested precision is not high; this is the case of two systems that differ in the number of machines. In this case, the difference between the systems is so high that a rough method is sufficient to know which configuration is better.

After evaluating the indicator that the firm wants to maximise, the alternative systems of the set are compared to each other by means of pairwise statistical tests. Since performance indicators can be affected by variability due to the uncertainty of demand, processing times, machine failures, error of the tool used to evaluate the indicator (e.g., the error of an approximated analytical method), etc., the comparison must take into account all the different sources of variability. Unprofitable solutions are then discarded from the analysed set of alternative systems while the others are assessed better in the following level $l + 1$ in detail.

It is worth noting that the consistency of the choices taken at each level is preserved by the hierarchical decomposition of the problem. Every decision taken at a level of the hierarchy is consistent with the whole problem and affects the decisions of the lower levels. The hierarchy preserves from discarding solutions in level l that can be profitable if they would be analysed in deep details at lower levels $l + 1$, $l + 2$, etc.

In summary, the method starts from an initial set of alternative production systems and continues until the most detailed level, the lowest one of the hierarchy, is reached providing a final set of system alternatives among which the manager can take the decision. At each level of the hierarchy, a different tool is used to evaluate the performance indicators of the system alternatives of the set and statistical tests are then used to compare them. How to compare system configurations and move from one level to the other is described in the following section.

3. Comparison of alternative production systems

Let us denote by Ω_l the set of alternative production systems that have to be evaluated at level l and let h_k be the performance indicator related to system k (with $k = 1, \dots, K$) that the firm desires to maximise. Since the system performance is affected by random events such as demands and machine failures, h_k is a random variable and our goal is to compare alternative configurations based on their expected values (with respect to the random events) $E[h_k]$, or an estimate of the expected value (variance is not considered). Furthermore, the method used to evaluate the system performance is typically approximate and is prone to errors. It is plausible to

think that, this error which is intrinsic to the system is also a random variable. Let us denote by ρ_l this random variable. ρ_l typically consists of two components, a constant c_l (representing a systematic over/under estimation) and a random variable ε_l which can be assumed to be normally distributed with zero mean. In general, this error can also depend on the value of the performance index (20% overestimation of capacity for instance) or on the random events. We suppress this dependence for the exposition of the approach but the method extends in an obvious way to more general error terms.

The comparison of two candidate configurations then takes on the following forms depending on the initial model and the level of analysis:

Case 1: $E[h_k]$ can be obtained exactly, and the error ρ_l is a constant ($\varepsilon_l = 0$). This is obviously the simplest case that can happen. In this case, the comparison of two configurations j and k reduces to the comparison of the respective means of h_j and h_k .

Case 2: $E[h_k]$ can be obtained exactly but the error ρ_l is a random variable. In this case, we cannot compare two configurations solely based on the means of the performance measures. On the other hand, it is assumed that $\varepsilon(\rho_l)$ is a normally distributed random variable with mean 0 and variance (σ^2). The comparison of two configurations j and k is then the comparison of two normally distributed random variables with respective means $E[h_j]$ and $E[h_k]$ and a common variance (σ^2). Note that case 1 is a particular case of case 2.

Case 3: $E[h_k]$ cannot be obtained explicitly and the error ρ_l is a constant. In this case, the mean value of the performance measure has to be estimated. To this end, we propose to generate R samples of random events (for instance, demands) and calculate $h_{k,r}$, a realisation of the random variable h_k for the sample r . We can then estimate $E[h_k]$ by the sample mean of individual realisations. In order to compare two configurations in this case, we use a paired nonparametric test such as the sign test or the signed rank test on the paired observations $h_{j,r}$ and $h_{k,r}$. The test result then enables us to say that configuration j is better than configuration k for a certain statistical significance level.

Case 4: $E[h_k]$ cannot be obtained explicitly and the error ρ_l is a random variable. This is clearly the most challenging case. To estimate $E[h_k]$, we need to advance as in Case 3, by generating R samples of random events and evaluating the realisation $h_{k,r}$. In order to handle the error ρ_l , we propose generating R samples from ρ_l for each configuration k (which can be denoted by $\varepsilon_{k,r}$). The paired non parametric test for comparison of configurations j and k can then be carried out on the paired observations $h_{j,r} + e_{j,r}$ and $h_{k,r} + e_{k,r}$.

The above-described approach for comparing different configurations is fairly general and fits into several frameworks. A critical assumption is the knowledge on the error term of the performance evaluation method

employed at level l . It is envisioned that this error is assessed by comparing results with simulation, or by experience or can even be a prior belief on the accuracy of the method.

A final remark is on the filtering procedure between different configurations. To filter out unsatisfactory configurations, we propose the following rule:

- Rule. Configuration j can be eliminated from further consideration if there exists a (different) configuration k , whose performance is superior (in a statistically significant way). In particular, the null hypothesis can be tested “configuration j dominates all the other system alternatives of the set Ω_l ” against the alternative hypothesis, “at least one configuration k of the set Ω_l dominates configuration j ”.

It is necessary to take into account the fact that the result of the test depends on the $(K - 1)$ applications of pairwise comparison tests since each configuration j is compared with all the other configurations of the set Ω_l . In particular, type I and II errors of the test are affected by those of the single tests used in pair wise comparisons. It is necessary to consider this fact when the number of samples R , on the basis of which systems are compared, is evaluated [7].

4. Application to a real Case

4.1. Description of the system

The production system is an automated manufacturing system similar to FMSs in which parts are machined by general purpose CNC machining centers. Machines are identical and one or more carriers move pieces and tools through the system. Parts are moved between load/unload station and machines, while tools are moved between central tool storage and local tool storage of machines. The main difference with traditional parallel-machines FMS is that parts are not worked by only one machine, but by several machines following a linear path as in automated flow lines. Machines and fixtures are smaller than traditional ones since the working cube is

400 mm; this issue can lead to important savings in the investment cost incurred by the firm. In [8,9], a detailed description of the system is presented and an economical comparison of the system with competing alternative ones is carried out.

Only one part is mounted on a pallet, therefore the number of pallets flowing in the system corresponds to the number of parts released in the system. Fixtures are mounted on pallets and are dedicated to products; in the remainder of the paper the words “pallet” and “fixture” are used interchangeably to mean the same thing. Let us denote with the term “mini-line” a set of machines that perform operations on the same parts as in flow lines; each mini-line can machine one or more part types. The system can be logically decomposed into mini-lines and their configuration can be modified during the running of the system with reduced set up times. For instance, the system in Fig. 1 is divided into 2 mini-lines: the first one machines product A while the second one machines product B. Part carrier moves parts from the input buffer to the first machine of the mini-line; then each part, after having been worked by all the machines of the mini-line, is moved to the output buffer by the part carrier. The behaviour of the system is that of different flow lines that share common resources such as part carriers, tool carriers, tools and load/unload station. Unbalancing of operations in mini-lines must be evaluated in order to estimate the system performance. A management loading module allocates the products to the machines and decides the number of mini-lines of the system during the time [10].

4.2. Assumptions

We assume that the firm has already selected the mix of N products. All the technical information necessary to design the process plan of each part type i of the mix (with $i = 1, \dots, N$) is available. It is reasonable that, if products and type of machines are known, technicians are able to define the whole process. Let us denote with $t_{i,j}$ the deterministic processing time of operation j of product i , with T_i the total processing time of product i and w_i the number of working positions of product i . Since all the system components such as machines,

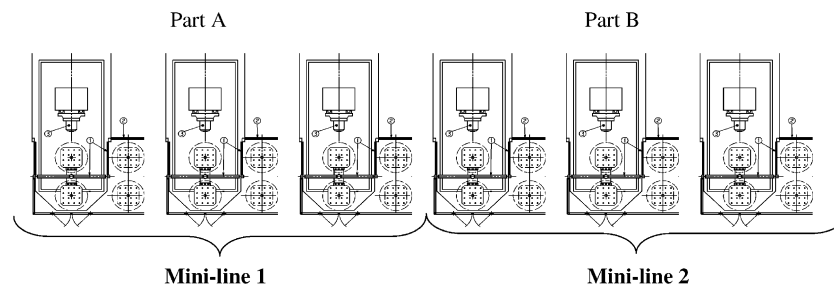


Fig. 1. Decomposition of the system into 2 mini-lines.

carriers, fixtures, etc., are assumed to be reliable, there is no variability in the behaviour of the system. Moreover, we assume that, if new products arrive in the future, they will be machined by other production systems of the shop floor and that the actual products of the mix will be produced during the whole planned time horizon T .

The type of production system has already been selected and corresponds to the one described above. Further we assume that the firm takes its decision of maximising the expected value of the net present value (NPV) of the investment defined as the actualised sum of cash flows related to the investment in the planned time horizon:

$$NPV = \sum_{t=1}^T \frac{\text{Cash Flow}(t)}{(1+r)^t}, \quad (1)$$

where r is the risk rate. Since types of machines, carriers, fixtures and tools are assumed to be known, the configuration problem statement is, *given the selected mix of products, allocate the system resources in order to satisfy the firm objectives*. That is, deciding the number of machines, part carriers, fixtures and tool carriers that maximise the expected value of the investment. Other system variables such as number of load/unload station, operators, etc are not considered here but the proposed approach is general enough to be extended to consider these aspects.

The market is subject to uncertainty: the firm has to forecast the market demand of its production mix. Uncertainty of demand is critical because errors in forecasts can lead to oversized systems (if future demand has been overestimated) or undersized systems (if future demand has been underestimated), strongly affecting the profitability of the investment. However, firms normally have some information on future demand. For instance, it is frequent that contract negotiation between supplier and customer, limits the demand variability defining some threshold values. In the automotive industry customers must often respect a maximum level of requested volumes defined in the contract [8,9], which becomes an upper bound on the demand; also the firm can forecast the lowest level of demand the market may request in the worst case. Therefore, demand is a stochastic variable but the firm often knows its variability range. If we indicate with the N -dimensional vector $\mathbf{D}(t)$, the market demand in the period $t = 1, \dots, T$ with U_i the known upper value with L_i the forecasted lower value, the inequalities $U_i \geq D_i(t) \geq L_i$ must be satisfied for each product i during the planned time horizon $t = 1, \dots, T$. In addition, we assume that demand is constant for any $t = 1, \dots, T$ and represents the long term average demand of product i ; therefore $D_i(t-1) = D_i(t) = D_i$ for $t = 2, \dots, T$ and the notation D_i is used in the following sections to indicate the market demand of product i in the planned horizon. A very strict constraint for firms is the infeasibility of

backlogging. It is assumed that, if capacity is not sufficient, the firm buys from other suppliers the parts that it cannot produce in the system since backlogging penalties are high.

We can write in detail the expression of the NPV followed by the notation used in the remainder of the paper:

$$NPV = (1-s) \sum_{t=1}^T \sum_{i=1}^N \frac{p_i D_i - c_{x,i} X_i(t) - c_{y,i} Y_i(t)}{(1+r)^t} - I_0 + \sum_{t=1}^T \frac{A(t)s}{(1+r)^t} + \frac{RV(t)}{(1+r)^T} (1-s), \quad (2)$$

where t is the time index, $t = 1, \dots, T$, $t_{i,j}$, the processing time of operation j of product i , T_i , the total processing time of product i , $RV(t)$, the residual value of investment in period t , I_0 the investment in period 0; $A(t)$, the depreciation of investment in period t , r , the risk rate, s , the tax rate, i , the product index, $i = 1, \dots, N$, D_i , the demand of product i in period t , $X_i(t)$, the production quantity of product i in period t , $Y_i(t)$, the outsourced quantity of product i in period t , $c_{x,i}$, the internal variable cost of product i , $c_{y,i}$, the external variable cost of product i , p_i , the revenue per unit part of product i .

4.3. Hierarchical decomposition of the problem

Given the high complexity of the problem and the infeasibility of considering all the decision variables at the same time, we apply the proposed methodology decomposing the main problem into four different sub-problems or levels. At each level, the production system is represented with a defined degree of detail and the tool used to evaluate the performance is coherent with the decision variables selected to describe the system (see Table 1).

It is assumed that the firm selects the production system that maximises the expected value of the NPV of the investment. Since demand backlogging is not considered, the expected value of revenues is constant for any system configuration that is analysed at the same level of demand; therefore, we can use the net present cost (NPC) as the discriminating indicator for selecting the most

Table 1
Decision variables and performance evaluation tools of the decomposed problem

Sub-problem	Decision variables	Performance evaluation tool
Level 1	Machines	Static analytical model
Level 2	Machines, part carriers	Static analytical model
Level 3	Machines, part carriers, fixtures	Dynamic analytical model
Level 4	Machines, part carriers, fixtures, tool carriers	Simulation

profitable alternative; NPC is defined as [8]:

$$\text{NPC} = (1 - s) \sum_{t=1}^T \sum_{i=1}^N \frac{c_{x,i} X_i(t) + c_{y,i} Y_i(t)}{(1 + r)^t} + I_0 - \sum_{t=1}^T \frac{A_t(t)s}{(1 + r)^t} - \frac{RV_T}{(1 + r)^T} (1 - s) \quad (3)$$

which represents the overall cost of the system during its life cycle. Investment cost I_0 is equal to the total costs of the resources of the analysed configuration.

One source of uncertainty of the problem is the market that requests products in accordance with a general statistical distribution. We assume that the values D_i of product demands, which are assumed to be constant during the planned horizon, are not correlated and that each one follows a statistical distribution limited in the interval $[L_i, U_i]$. In order to take into account of the market variability, R different values of demand are randomly generated for each product in accordance with the estimated distribution and we denote with \mathbf{D}_r the N dimension vector of demands that is generated for each sample $r = 1, \dots, R$. In such a method the overall performance of the system, that is measured by NPC, has to be calculated for each sample of the generated demand \mathbf{D}_r , in particular we have R samples of NPC for each configuration.

Starting from an initial set Ω_1 of system alternatives, at each level the method evaluates with expression (3) the performance indicator for each alternative. Since the detail of the analysis increases from the first to the fourth level, we need different methods to evaluate the system performance. In particular, approximate analytical methods that describe the production system statically are used in levels 1 and 2 of the hierarchy to evaluate the NPC with low computational efforts. When the complexity of the problem increases, more precise tools that model the system dynamically are used in levels 3 and 4, since we need more accurate results than in the higher levels.

The system alternatives of the set Ω_l are compared at each level l (with $l = 1, \dots, 4$) on the basis of the R samples of their NPC. The second source of variability of the problem, that is the error that each tool can do when evaluating the NPC of a certain configuration given the generated level of demand, is taken into account by the statistical test described in Section 3. Finally, the set of alternative systems among which the manager will select the production system is chosen in level 4. In the remainder of the section, the levels of the hierarchy are described.

Level 1: In the highest level of the hierarchy, each alternative system is described by the number of machines M . Let us denote with M^{\max} the maximum number of machines that can run in the system at the same time and with $\Omega_1 = \{1, \dots, M^{\max}\}$, the set that contains all the possible system alternatives. Investment cost is equal to

the costs of machines and M^{\max} can be provided by the system supplier that designed the system architecture or can be evaluated on the basis of the budget of the firm.

In order to evaluate the NPC of the configuration k (with $k \in \Omega_1$), it is necessary to know the throughput of the system and how many parts the firm buys from external suppliers. This is equivalent to solving the following linear programming problem that provides the values of X_i and Y_i , the quantities of each product to make or buy:

$$\min z = \sum_{i=1}^N c_{x,i} X_i + c_{y,i} Y_i$$

subject to:

$$X_i + Y_i = D_i \quad \forall i, i = 1, \dots, N \quad (c1), \quad (4)$$

$$\sum_{i=1}^N X_i T_i \leq HM \quad (c2),$$

$$X_i, Y_i \geq 0 \quad \forall i, i = 1, \dots, N \quad (c3),$$

where H is the time available for each machine. We assume that the firm minimizes, in the make or buy decision, the sum for each product of the variable costs, subject to the constraints of demand (c1) and capacity (c2); X_i and Y_i have nonnegative values. Firm prefers to produce those part types that, if they were bought from external suppliers, would have high penalty. Therefore, solving the above linear problem corresponds to rank part types on the basis of the penalty $(c_{y,i} - c_{x,i})/T_i$; products with high penalty are preferably machined in the shop floor, while products with low penalty are outsourced. To compare the alternatives of the set Ω_1 and to discard the less profitable ones, we must use the tests described in Section 3. For instance if distributions of NPC are known and the error, committed by the method when it evaluates NPC, is constant, it is possible to apply the test of case 1.

Level 2. In the second level of the hierarchy, each alternative system is described by the vector (M, P) , where M is the number of machines and P is the number of part carriers. The range of variability of M has been decided in the first level while the variable P can assume integer value in the interval $[1, P^{\max}]$, where P^{\max} is the maximum number of part carriers that can run in the system at the same time. Let us denote with Ω_2 the set of all the possible configurations that are compared in the level 2 of the hierarchy. In this level, the investment cost is equal to the sum of the costs of machines and part carriers and P^{\max} can be provided by the system supplier or limited by the budget constraint of the firm.

The quantities X_i and Y_i of each product are evaluated by solving the linear model described with (4) that considers the following additional constraint:

$$t_p \sum_{i=1}^N X_i w_i \leq HP, \quad (5)$$

where t_p is the average time to transport a part from the load/unload station to the machines and vice versa; w_i is the number of times that a piece of product i is moved by the part carrier to the machines and it is related to the fact that a product can need more than one working position to complete all the operations of the part program. One of the tests described in Section 3 can be used to compare the alternatives of the set Ω_2 and to discard the less profitable.

Level 3: In the third level, fixtures are considered as decision variables in addition to machines and part carriers. The system is described by the vector (M, P, F) , where F is a N dimension vector containing the number of fixtures dedicated to each part type. Let us denote with F_i^{\min} and F_i^{\max} respectively the minimum and maximum number of fixtures dedicated to part type i . F_i^{\max} corresponds to the maximum number of pallets that can flow in the system at the same time without blocks, while F_i^{\min} depends on the minimum throughput that the system must have in order to satisfy the demand F_i^{\min} and F_i^{\max} are equal, respectively $2a_i + 1$ and $3b_i - 1$, where a_i is the minimum number of machines necessary to produce the peak volume and b_i is the number of machines of the mini-line that machines the product i . Let us denote with Ω_3 the set of all the possible configurations that are compared in the level 3 of the hierarchy. Investment cost is equal to the sum of the costs of machines, part carriers and fixtures.

In the third level of the hierarchy, input data are more detailed since the processing times of each operation $t_{i,j}$ are considered for each product instead of the total time $T_i = \sum_j t_{i,j}$. Moreover the performance evaluation tool represents the system, taking into account the possibility of splitting the set of machines into mini-lines. Therefore mini-line unbalancing is considered when the throughput of the system is evaluated by means of state equations that model the behaviour of pallets flowing in mini-lines. The quantities X_i and Y_i of each product are evaluated minimising the function z of the problem (4) subject to the constraints of limited number of machines, part carriers and fixtures. After the loading of parts to the machines, the analytical method described in [11] evaluates the throughput of the system. Tests described in Section 3 can be used to compare the alternatives of the set Ω_3 and to discard the less profitable ones.

Level 4: In the last level, tool carriers are included as decision variables in addition to those considered in the previous sub-problem. The system is described by the vector (M, P, F, T) , where T is the number of tool carriers of the system. Let us denote with Ω_4 the set of all the possible configurations that are compared in the last level of the hierarchy. In this level, the investment cost is equal to the sum of the costs of machines, part carriers, pallets and tool carriers. The simulation model described in [11] evaluates the performance of the system for a given

configuration of the tool storage. In this particular case, the results provided by simulation are not affected by error since it is assumed that time is deterministic, machines are reliable, routing of parts is known, etc. Tests in Section 3 can be used (in particular those described in cases 3 and 4) depending on the information available on demand, to compare the alternatives of the set Ω_4 and to discard the less profitable, providing to the decision-maker the final set of production systems.

5. Conclusions

An integrated approach to dimension automated manufacturing systems has been proposed in the paper. The method is based on the hierarchical decomposition of the problem into different sub-problems, each one defined by its level of detail. The accuracy of the analysis increases from the top of the hierarchy to the lower levels while the complexity of the problem decreases. Each sub-problem can be solved with a different technique depending on its level of detail.

The stochastic nature of the problem is considered together with its complexity, taking into account of the different sources of variability such as market demand and system behaviour. The large set of alternative production systems is not exhaustively investigated since most of the configurations are discarded by the application of statistical tests. The whole approach is not limited by particular assumptions, but it is flexible enough to use all the information that is available on the problem, improving the level of the analysis. The method has been applied to a new type of manufacturing system called MFP but it can also be used for other production systems such as transfer lines, flexible manufacturing systems and cellular manufacturing.

Future work needs to be done to assess the benefits of the method proposed. In particular, numerical work on the real case will be carried out as well as applications to other production systems. Another interesting extension would be to compare the alternative production systems on the basis of different indicators. For instance some measures related to the variance of the selected performance indicator, in addition to the already considered expected value, could be used to compare the systems.

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