A simulation-expert-system-based approach for machine sizing of production systems

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Abstract

Purpose – The purpose of this research is to focus on the solution of the resource sizing problem for production systems (PSs), defined as the specification of the number of each type of resources to be used in a production process for a given time period.

Design/methodology/approach – The resource sizing problem is tackled by a simulation-expert-system-based approach, coupling an expert system (ES) with a simulation tool. Hence, a number of "simulation – ES optimization" cycles are realized until obtaining non-improvable levels of performance. The main performance measures considered in this work are related to the manufacturing orders due dates (DD).

Findings – Through the approach proposed in this work, it is possible to size machines in order to optimize DD related performance measures for a PS belonging to a specific application domain. PSs of this domain are characterized by a functional layout and feature no labor constraints. In addition, machines belonging to a same department are considered to be identical.

Originality/value – The developed approach allows studying the machine sizing problem realistically, through the use of stochastic simulation. Also, by coupling an ES to the simulation tool, it avoids the try and error aspect characterizing most simulation-based approaches. It hence features a well-structured reasoning mechanism for the search of the best solution.

Keywords Resource allocation, Manufacturing systems, Simulation, Performance measures

Paper type Research paper

Introduction

This research is interested in one of the major design issues of production systems (PSs): the resource sizing problem. It is defined as the specification of the number of each type of resources to be used in a production process for a given time period (Miller and Davis, 1977). Sizing is required while designing a new or expanding an existing system (Feyzioglu *et al.*, 2005). The approaches that tackled this problem can be classified in two principal categories: analytical and simulation-based.

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The former is based on mathematical models connecting parameters like production needs and resource capacities to the required resource quantities. De Matta *et al.* (1999) developed a "Branch-and-bound" algorithm for resource sizing within a flexible manufacturing system (FMS) to minimize the resource costs along with tardiness penalties. In addition, Lin and Yang (1996) proposed a multi-criteria approach using the analytic hierarchy process (AHP) method for the sizing of the most suitable machine from a range of machines available to manufacture a particular type of parts. Nevertheless, the major disadvantage of the *quasi*-totality of these approaches is their static aspect. Moreover, these approaches do not consider the dynamic and the stochastic aspects inherent to certain factors like demand and manufacturing time variation or the reliability of resources. Also, these approaches offer a very poor global view of the studied system since they tackle the resource-sizing problem independently from other problems such as scheduling, layout and material handling. So, the obtained results lack robustness. In addition, to study real case problems, the enormous amount of required data makes the mathematical formulations too complex to handle. Moreover, other analytical approaches were used in conjunction with artificial intelligence methods such as expert systems (ESs). In fact, Kusiak (1987, 1990) used an ES to decide, according to the available data and problem size, which mathematical model and which resolution algorithm to use. Though, the weaknesses mentioned before are always present in spite of the intelligent aspect of the approach.

The second category encloses simulation-based approaches such as the work of Bullinger and Sauer (1987) who determined, by simulation and in an iterative way, the resource quantities for the system to be sized until obtaining a satisfactory state. Equally, Dumbrava (1997) used simulation to determine the number of machines of an FMS in order to minimize the work in process, and to obtain a good compromise between the capacity and the productivity of the system. In the same context, Peng *et al.* (2001) and Choi *et al.* (2002) used simulation to select the best of many pre-designed scenarios to design a PS. Also, Patel *et al.* (2002) investigated ways of increasing the throughput of a PS by simulating its operation with various levels of machines and labor. Nevertheless, the main drawback of the majority of this kind of approaches is their strong bond with "try and error". On the other hand, simulation-optimization methods have been applied to various sizing problems. Pierreval and Tautou (1997) sized the number of resources of a food industry facility using an evolutionary algorithm in conjunction with a simulation model. Similarly, Spieckermann *et al.* (2000) coupled genetic algorithms (GA) and simulated annealing with their simulation model for the design of an automotive manufacturing plant. Also, Cheng and Feng (2003) developed a new mechanism that integrates simulation with GA to find the best resource combination for a PS. Equally, Chan *et al.* (2000) developed an integrated approach for the automatic design of FMSs using simulation and AHP. Nevertheless, the use of methods such as GA or AHP helped sorting out the best solution from a very big number of possible scenarios, but did not structure the decision process. More recently, Feyzioglu *et al.* (2005) formulated the PS sizing problem as a constrained multi-objective optimization problem and tackled it by simulation in conjunction with a bootstrap approach which accounts for the stochastic aspect of the problem. Besides, in order to systematize the decision-making process for the solution of the job shop resource sizing problem, Chtourou and Guillot (1993) proposed an approach based on the integration of simulation and an ES. Their simulation-expert-system-based approach (SESA) permits to obtain the performance levels set by the user through a well-structured reasoning mechanism. However, it is deterministic and based on irrelevant cost-related performance measures.

The main objective of this work is to develop an enhanced version of the SESA for the machine sizing of functional-layout-based manufacturing systems. The proposed approach is based on performance measures related to the degree of compliance with manufacturing orders (MO) due dates (DD). It does not any longer require the setting of target performance levels, since it seeks obtaining non-improvable ones. Moreover, this study considers the stochastic aspect which governs MO launching as well as machine operating parameters.

The remaining of the paper is organized as follows: the next section describes the basic features of the SESA. Subsequently, the essential elements of the developed simulation model are depicted under the section, PS modeling for simulation. Next section, ES, provides a brief description of the ES that served to assess the performance measures in order to suggest relevant modifications to the PS being sized. Then, an illustrative example of the SESA application is presented under the section, illustrative example. Finally, conclusions and future work prospects are discussed in the last section.

Proposed approach

Concept

Three main types of information are required for the application of the SESA: PS data, demand pattern and performance limits (Table I).

The simulation tool uses the PS data and demand pattern to simulate the realization of a typical set of MOs over a given planning horizon. Simulation results are then considered as performance measures of the system. These results, in addition to the performance limits and relevant PS and demand pattern data constitute the ES required inputs. The ES is in charge of analyzing the PS situation. If the simulated system performance is found to be improvable, the ES recommends a modification to its resources in order to overcome the problem considered to be responsible, at the largest extent, for the low performance. Consequently, a new cycle is run until the ES becomes unable to suggest any modifications (Figure 1). Finally, it is worth noting that the approach can be started from any initial PS configuration assuring the feasibility of all MOs.

Domain of application

Despite the fact that the proposed approach is not restricted neither to one type of resources nor to a particular layout, this paper is focused on the specific machine sizing problem of a job shop type PS. This type of PS is said to be functional-layout-based. Hence and since no labor constraints are taken into account, operators are supposed to be always available when needed. Moreover, in the adopted job shop layout, functionally similar machines are grouped into departments where all machines are supposed to be operationally identical. Also, all products are manufactured and handled by batches of a constant size. Finally, the material handling system is bi-directional and the distances between same department machines are negligible compared to the ones separating departments.

Type of information	Details
PS data	Number of departments Initial quantity of resources within each department Material handling system characteristics (capacity and speed) PT and ST on all workstations for relevant product types
Demand pattern	Batch inter-arrival times (time intervals between MO launchings) For each MO: Product type BS Routing (sequence of required operations) Due date (DD_p)
Performance limits	Maximum and minimum URs for each department Significance threshold (*S* percent): a percentage of the aggregate DD

Table I.
Required information for the SESA application

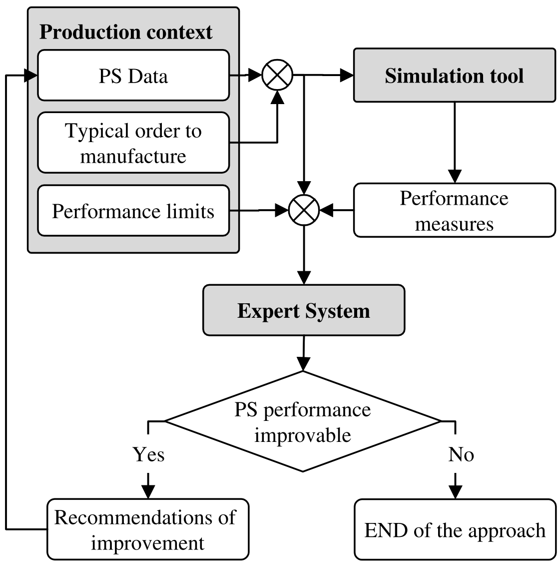

Figure 1.
Overview of the SESA

Performance measures

Most of the simulation-based sizing researches aim at maximizing the system throughput or at minimizing the amount of work in process. Some other studies focused on minimizing the inventory cost or on the global cost minimization. Unfortunately, in practical applications, it is extremely difficult to define a realistic cost function (Feyzioglu *et al.*, 2005). Besides, in a competitive "make to order" context characterizing the PSs of the job shop type, it is common to consider the degree of compliance with DDs as a main objective. In fact, tardiness minimization leads to the delay penalties minimization, whereas storage costs minimization could be achieved through earliness minimization. Furthermore, in order to avoid superfluous investment costs, all resources should be fully utilized.

Hence and since tardiness is usually considered as a more critical problem, the present study mainly targets the minimization of tardiness while earliness minimization is considered as a secondary objective. Moreover, while trying to attain both objectives, all resources are subjected to a minimal and a maximal utilization rate (UR) constraints. For each resource, the former depends on its investment cost whereas the latter indirectly accounts for its availability. Hence, respecting both constraints for each resource insures that its acquisition is relevant and that its utilization level is realistic.

Besides, tardiness (earliness) could be assessed by the mean batch tardiness (earliness) MT (ME) or also using the average number of batches tardy (early). Extensive simulations, carried out in various contexts, showed that MT and ME are by far more informative of the PS state (Masmoudi *et al.*, 2004). Also, it is worth mentioning that each MO DD is obtained by multiplying its total work contents (TWK) by a user defined factor K. TWK is the sum of all processing and transportation times required to complete the MO in an ideal situation where neither waiting nor setup are required, whilst K expresses the DD strictness as required by the user. Furthermore, another performance measure is crucial for the determination of the department representing a potential bottleneck: it is the average number of batches waiting in machine queues (nw). Nevertheless, in the presence of two departments having practically the same nw, the average waiting time of these batches in machine queues (wt) is used as tiebreaker. Finally, and for the sake of statistic reliability, the overall system throughput is used as the steady state detection performance measure.

Production system modeling for simulation

The production of the typical MO pattern by the PS being sized was modelled for simulation using the commercial tool arena (*User's Guide*, 2002). The model involves three main components discussed in the following subsections (Figure 2(a)).

MOs launching

The entry of the product batches to the PS is realized by a module that generates individual parts at a frequency governed by an appropriate statistical rule. These parts are then congregated into batches of a given size just after operational attributes being assigned to them. These attributes are mainly the product type, the batch size (BS), the processing and setup times (ST) on all relevant workstations as well as the corresponding routing. After that, the batches are transported towards the first target department as determined by the corresponding routing (Figure 2(b)).

Batch processing

The first task to be performed when a batch enters a machine department is the selection of the most available machine. Such a machine is the one having the minimum number of products in queue and in process. However, parts processing requires a prerequisite batch splitting operation, and is followed by a reconstitution of the original batches. In addition, every machine is modeled by a process type module. When such a module receives a part, it seizes an available resource for a time period

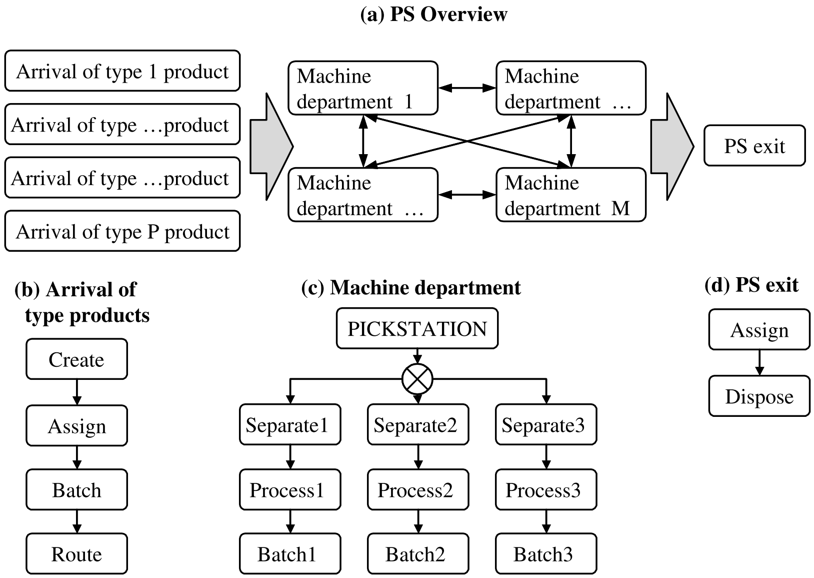

Figure 2.
PS simulation model

corresponding to the sum of loading/unloading and process times (PT). Additional ST are also accounted for if the current part product type is different from the previously processed one. The seized machine resource is subsequently released and becomes eligible to receive another part. Furthermore, batches arriving at a busy machine wait at its queue until it becomes available (Figure 2(c)).

System exit and performance measure gathering
Lastly, before a batch leaves the PS, it should go through an assignment module in order to allow computing and actualizing the values of parameters defined as performance measures and presented earlier in this paper (Figure 2(d)).

Expert system

The developed ES is an object-oriented decision-making tool. It is composed of four main parts. First, the object base is the "static knowledge" component. The objects are organized hierarchically into classes and sub-classes representing all problem elements such as global PS data and departments of machines (Abel and Abel, 1988). Thus, the *department i* object is a sub-class of the class "Departments of machines" which is in turn a sub-class of the "Resources" class. Besides, the rule base is the ES component representing the "know-how". This expertise is expressed in terms of inference rules of the form: "IF [condition] THEN [action]" grouped in several packs, each representing one of the main functions of the ES (Figure 3). These are:

- *Checking PS global state.* The ES verifies that the global performance measures are within the prescribed limits and that they did not significantly worsen compared to the last cycle levels.

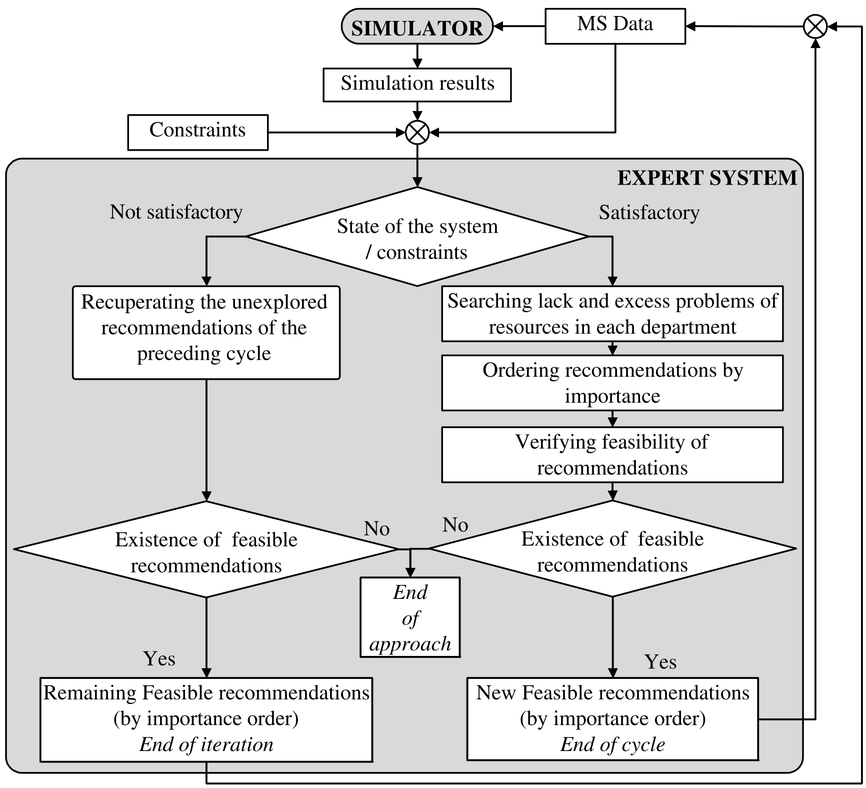

Figure 3.
ES problem solving scheme

- *Determining a new ordered problem list.* In case the global PS state is judged to be acceptable, the ES searches for the potential lack/excess of resource type of problems.
- *Formulating a new ordered recommendation list.* For each problem from the determined list, the ES suggests a feasible solution, if any. For the sake of stability, only the first solution from the obtained list is applied in the next simulation run.
- *Recuperating the remaining of last cycle recommendation list.* In case the global PS state is judged to be unacceptable, the last cycle modification is canceled and the ES suggests the remaining of last cycle recommendation list.

Hence, the ES inference engine exploits both static and dynamic knowledge in order to generate recommendations for PS resource modifications using a deductive reasoning mechanism known as forward chaining. Besides, it is worth mentioning that the iterative functioning of the approach consists of a sequence of cycles, each comprising one or several iterations. Each iteration is an attempt to adopt one of the last cycle recommendations. It may lead to the end of the cycle if the corresponding recommendation is retained or else to the following iteration. The absence of any recommendations after feasibility checking means the end of the approach (Chtourou *et al.*, 2005).

Finally, all simulation results as well as user prescribed performance limits are introduced via the ES user interface that serves also to communicate recommendations about changes in resource quantities.

Illustrative example

A simple case study is here presented as an illustrative example of the SESA application. The main characteristics of the PS and the demand pattern used in this example are recapitulated in Table II whereas the simulation results for the first cycle (0) are shown in Table III. In addition, the transport time between departments is equal to 10 min. Also, it is worth mentioning that the arrival of batches is generated by a "Poisson" law whereas the setup of the machines follows a triangular law of distribution (Newman and Maffei, 1999).

The second phase of the same cycle 0 is the PS performance analysis carried out by the ES. The latter established that the PS performance is improvable since the global mean tardiness is above the acceptance threshold corresponding to 3 percent of the aggregate DD. It then started to search for problems of lack or excess of resources in each department. According to Table III, department M3 is the most overloaded among the five departments since it has the greatest nw. Consequently, the recommendation suggested for this cycle was: "adding up of one machine in department M3". Similarly, seven cycles were necessary to reach a non-improvable performance level. Their respective results are summarized in Table IV.

Hence, adopting a notation where machine quantities of the five departments (M1 to M5) are separated by "/", the best solution was [2/1/4/3/1]. It is also worth noting that the ES suggested adding up a machine to department M3 despite the negligible value of MT at the end of the sixth cycle (7 minutes). Such an addition was justified by the very high UR of department M3 (99.6 percent). Thus, the final solution presents definitely a much improved performance as shown in Figure 4.

Moreover, as a preliminary validation of the SESA, the same example was studied by the optimization tool Optquest integrated in the Arena simulation software. This tool uses optimization techniques that are not unveiled to users and offers much less flexibility than the developed ES. In fact, only one objective could be addressed at a time. So, for the studied example and with "MT minimization" set as main objective, the best solution reached after 150 iterations was: 2/1/5/3/1. Hence, even with a higher computational cost, the obtained solution is more "expensive" in terms of machines than the one determined by the SESA.

In addition, the approach was applied with a different initial PS [2/2/3/3/1] in order to study its effect on the final solution. The latter was found to be identical to the previously determined one and it was reached with only three cycles (Table V). Thus, the initial PS does not seem to have an influence on the final solution, but it has an effect on the number of cycles.

Complementary simulations also showed that the choice of the threshold S can influence the final solutions of the SESA. In fact, referring to Table V, if S becomes 10 percent, the final solution could have been [2/2/3/3/1]. So, it is up to the PS manager to choose between investing in more machines even if they are not fully utilized

Table II. Example required information

	Details						
	Department	*Product type*	*PT (min)*	*ST (min)*			
PS data	M1	P1	5	Triangular (20, 25, 30)			
		P3	5	Triangular (20, 25, 30)			
	M2	P1	3	Triangular (25, 30, 35)			
		P2	3	Triangular (25, 30, 35)			
	M3	P1	12	Triangular (115, 120, 125)			
		P2	10	Triangular (95, 100, 105)			
	M4	P2	7	Triangular (100, 105, 110)			
		P3	10	Triangular (145, 150, 155)			
	M5	P3	5	Triangular (70, 75, 80)			
	Product type	*Routing step*	*Department*	*BS*	*Inter arrival law (min)*	*TWK (min)*	*DD_p (min)*
Demand pattern	P1	1	M3	10	Poisson (120)	220	2,200
		2	M1				
		3	M2				
	P2	1	M2	10	Poisson (120)	220	2,200
		2	M3				
		3	M4				
	P3	1	M1	10	Poisson (120)	220	2,200
		2	M4				
		3	M5				
	Limit	*Value (percent)*					
Performance limits	UR^{a}_{min}	20					
	UR^{a}_{max}	90					
	S	3					

Note: [a]For each department

and this, in order to further minimize MT (very low *S*), or accepting a slightly MT in order to save on investments (fairly high *S*).

Conclusion

This study presented an enhanced version of the SESA coupling an ES and a simulation tool for the machine sizing of a PS. The current version uses performance measures that are adapted to the DD characterized "make to order" production context. It also allows for considering the stochastic aspect governing several manufacturing facets. The approach permitted to obtain satisfactory preliminary results in the sizing of a simple PS belonging to predefined domain of application.

Finally, many aspects of the approach are currently being developed. They mainly are:

- Enlargement of the domain of application and consequently, enrichment of the simulation model by incorporating other types of resources and by considering resource reliability and routing flexibility. This should allow applying and validating the approach on real cases.
- Enrichment of the reasoning mechanism by incorporating new knowledge acquired from sets of planned simulations.
- Thorough investigation of the approach robustness and applicability in various scenarios.

Table III.
Simulation results of cycle 0

MT = 28,548 minutes			
Department	Machine number	nw (batches)	UR (percent)
M1	1	0	73.2
M2	1	0	49.5
M3	1	670	100
M4	1	231	100
M5	1	0	8

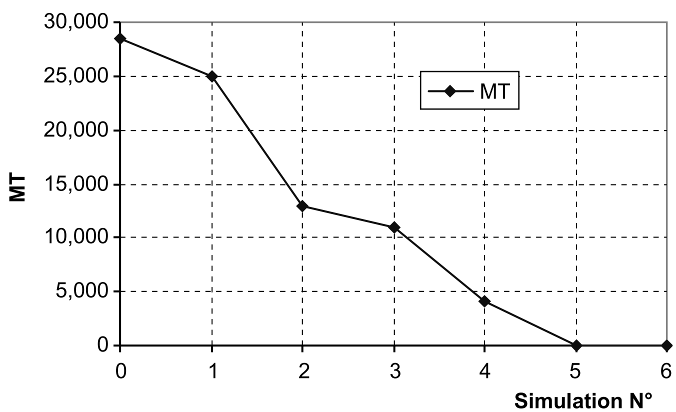

Figure 4.
MT evolution

Table IV. Results of the various cycles

Cycle number	M1	M2	M3	M4	M5	MT	ME	ES recommendation
	Machine number							
0	1	1	1	1	1	28,548	1,838	+M3
1	1	1	2	1	1	24,935	7	+M4
2	1	1	2	2	1	12,993	43	+M3
3	1	1	3	2	1	10,966	0	+M4
4	1	1	3	3	1	4,061	606	+M1
5	2	1	3	3	1	7	1,090	+M3
6	2	1	4	3	1	0	1,838	End

Notes: +machine adding up; − machine removal

Table V. Results of the various cycles with a different initial PS

Cycle number	M1	M2	M3	M4	M5	MT	ME	ES recommendation
	Machine number							
0	2	2	3	3	1	341	964	+M3
1	2	2	4	3	1	0	1,854	− M2
2	2	1	4	3	1	0	1,835	End

Notes: +machine adding up; − machine removal

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