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Labor and machine sizing through a Simulation-Expert-System-based Approach

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Abstract

This work presents the development of an enhanced version of the Simulation-Expert-System-based Approach (SESA) previously used to solve the manufacturing system (MS) machine sizing problem. The SESA is improved by considering operator sizing along with machine sizing. The proposed approach consists in coupling an expert system (ES) with a simulation tool. The main performance measures considered in this work are related to the manufacturing orders due dates. Accordingly, labor resources are now implemented in the MS simulation model and ES reasoning mechanism is adjusted in order to optimise both machine and operator quantities. Finally, an illustrative example showed the potential benefits of the approach enhancements through the enrichment of both simulation model and the expert system reasoning mechanism.

Keywords: Machine sizing; Labor sizing; Simulation; Performance measures; Expert system

1. Introduction

The fierce competition in the industrial field impels the manufacturers, throughout the world, to continuously review their methods of manufacturing systems (MS) design and operation. This research work is interested in one of the major MS design issues, required while designing a new or expanding an existing system [1]. It is related to the resource sizing problem defined as the specification of the number of each type of resources to be used in a production process for a given time period [2].

The approaches that tackled this problem can be classified in two principal categories: analytical and simulation-based. Approaches belonging to the first category are based on mathematical models that oversimplify the studied MSs. Whereas, approaches of the second category ensure a more realistic representation of the manufacturing contexts even though many of them are strongly related to "trial and error". Some other

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simulation-based approaches integrate optimization and/or decision aiding tools in order to systematize and to structure the decision making process. One of these promising approaches is the Simulation-Expert-System-based Approach (SESA) proposed by Chtourou and Guillot [3] and enhanced by Masmoudi et al. [4] and by Chtourou et al. [5]. Nevertheless, despite the several benefits of its latest version, SESA and the quasi-totality of similar approaches fail to consider the labor resources. However, in addition to its intrinsic importance, this issue is proved to be strongly consequential for accurate determination of machine requirements [6]. The main objective of this work is to enhance the SESA in order to include sizing of labor resources along with machines.

The remaining of this paper is organized as follows: Section 2 presents a review of the MS sizing literature. Section 3 gives a general presentation of the SESA and its field of application. A discussion of the used performance measures is also provided in the same section. Section 4 presents the new simulation model including labor resources while Section 5 gives a general overview of the ES along with a description of its improved reasoning mechanism. An illustrative example showing the capabilities of the enhanced version of the SESA is depicted in Section 6. The final section is dedicated to the general conclusion and the future work prospects.

2. Literature review

Analytical approaches for MS sizing are based on mathematical models connecting parameters like production needs and resource capacities to the required resource quantities. Among the recent studies belonging to this category, Lin and Yang [7] proposed a multi criteria approach using the analytic hierarchy process method (AHP) for the sizing of the most suitable machine from a range of machines available to manufacture a particular type of parts. In another work, De Matta et al. [8] developed a ‘‘Branch-and-bound’’ algorithm for resource sizing within a flexible manufacturing system (FMS) to minimize the resource costs along with tardiness penalties. Nonetheless, the main weakness of the quasi-totality of these static approaches is their oversimplification of the studied system. Moreover, they do not consider the stochastic aspects inherent to certain factors like demand, processing time variation or resources reliability. Consequently, the obtained results lack robustness and studying real case problems through these approaches turn out to be very hard due to the cumbersome mathematical formulations.

Other analytical approaches were used in conjunction with artificial intelligence methods such as expert systems (ES). In fact, Kusiak [9,10] used an ES to determine, according to the available data and problem size, the best available mathematical model and the best associated resolution algorithm to use. Yet, regardless of the additional intelligent aspect, the above mentioned shortcomings remain present.

The second category of sizing approaches includes simulation-based approaches such as the work of Patel et al. [11] who investigated ways of increasing the throughput of a MS by simulating its operation with various levels of machines and labor. Similarly, Choi et al. [12] and Peng et al. [13] used simulation to select the best of many pre-conceived scenarios to design a MS. Also, Dumbrava [14] used simulation to determine the number of machines of a FMS in order to minimize the amount of work in progress and to obtain a good compromise between the capacity and the productivity of the system. In the same context, Bullinger and Sauer [15] iteratively determined, by way of simulation, the resource quantities for the system to be sized until obtaining a satisfactory state. Still, the main drawback of the majority of approaches belonging to this category is their reliance on ‘‘trial and error’’.

Simulation-optimization methods have been utilized in various sizing problems. In fact, Cheng and Feng [16] developed a new mechanism integrating simulation and genetic algorithms (GA) in order to optimize a MS resource combination. Also, Chan et al. [17] developed an integrated approach for the automatic design of FMSs using simulation and AHP. Similarly, Spieckermann et al. [18] coupled GA and simulated annealing with their simulation model for the design of an automotive manufacturing plant. Similarly, Pierreval and Tautou [19] sized the number of resources of a food industry facility using an evolutionary algorithm in conjunction with a simulation model. Even though, the use of methods such as GA or AHP helped sorting out the best solution from a very large number of potential scenarios, it did not structure the decision process. More recently, Feyzioglu et al. [1] formulated the MS sizing problem as a constrained multi-objective optimization problem and tackled it by simulation in conjunction with a bootstrap approach that accounts for the stochastic aspect of the problem.

In order to systematize the decision-making process for the solution of the Job Shop resource sizing problem, Chtourou and Guillot [3] proposed a Simulation-Expert-System-based Approach (SESA) permitting to obtain the performance levels prescribed by the user through a well organized reasoning mechanism. However; this approach is deterministic and based on irrelevant cost-related performance measures. Masmoudi et al. [4] overcame this limitation by proposing a version of this approach using a stochastic simulation tool and due date related performance measures. Nevertheless, their work did not consider labor constraints which constitute a serious limitation for the approach application. In fact, these constraints are intensely consequential for accurate determination of machine requirements [6].

3. SESA description

3.1. Overview

SESA application requires three main types of information: MS data, demand pattern and performance limits (see Table 1). The simulation tool uses the MS data and demand pattern to simulate the realization of a typical set of manufacturing orders (MO) over a given planning horizon. Simulation results are then considered as performance measures of the system. These results, in addition to the performance limits as well as the MS data and the demand pattern constitute the ES required inputs.

The reasoning mechanism of the ES is split into two main stages (see Fig. 1):

- *Stage 1*: Machine sizing, with no labor constraints.
- *Stage 2*: Labor sizing in accordance with the machine solution determined in stage 1.

In fact, the ES first starts with analyzing the MS machine situation without any labor constraints. Hence, this first stage assumes the maximum labor capacity by assigning an operator to every machine. If the simulated system performance is found to be improvable, the ES recommends a modification regarding the machine quantities in order to overcome the problem considered to be the most responsible for the low performance of the MS. Consequently, a new cycle is run with the modified machine quantities until the ES is no more able to suggest any modifications. This situation corresponds to the end of the first stage. In the second stage, the ES is set to size the MS labor in accordance with the machine solution obtained at the end of the first stage. Again, optimization cycles are run until reaching a non improvable MS. These cycles consists of performance measure analysis followed by labor modification and then simulation.

Besides, the first stage can be started from any initial MS machine configuration assuring the feasibility of all MOs. As for the second stage, the initial operator solution is determined through a simple proportionality rule aiming at approaching the final solution as much as possible. Hence, if for each department d, N_{d} is the

Table 1
SESA input

MS data
• Number of machine departments.
• Material handling system characteristics (capacity and speed).
• Process (PT) and setup times (ST) on all machines for each product types.
Demand pattern
• Batch inter-arrival times (time intervals between MO launchings).
• Product type of each MO.
• Batch size (BS) of each MO.
• Routing (sequence of required operations) of each product type.
• Due date (DD_p) of each MO.
Performance limits
• Maximum and minimum utilization rates for each department.
• Significance threshold (S%): a percentage of the aggregate DD.

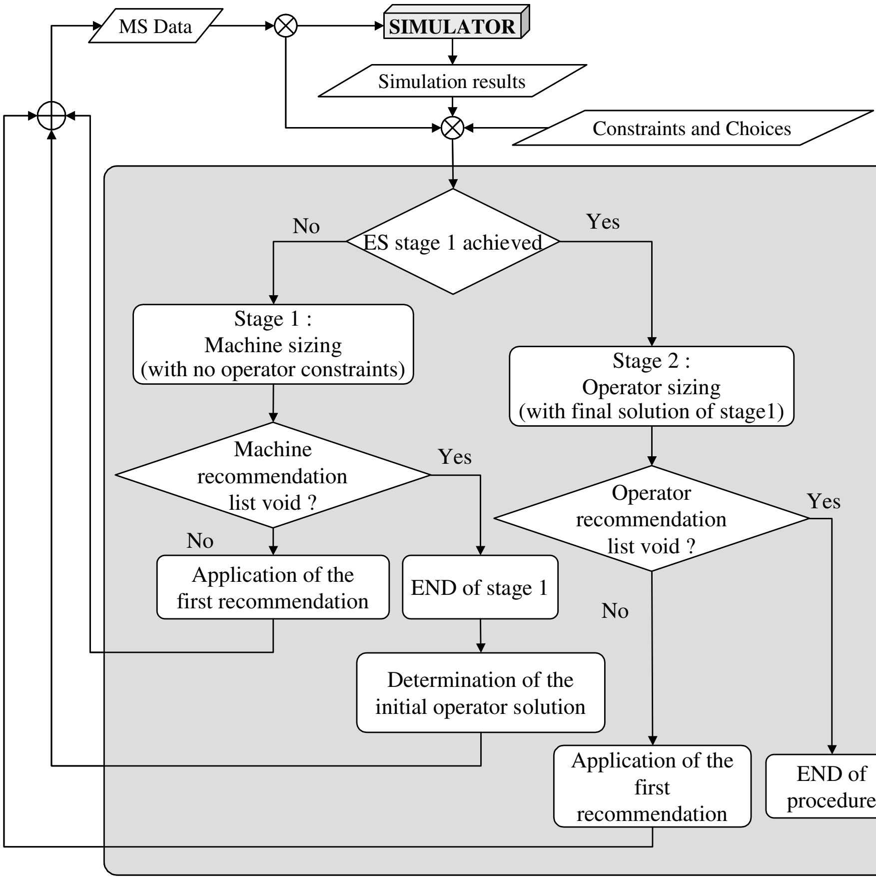

Fig. 1. SESA overview.

number of operators (initially corresponding to the number of machines in the 1st stage) and UR_{Ld} is the associated aggregate labor utilization rate, the procedure is as follows:

$$\left|\begin{array}{l}\text{While}\left[(N_{\mathrm{d}}>1)\ \text{AND}\ \left(UR_{\mathrm{Ld}}\times\left(\frac{N_{\mathrm{d}}}{N_{\mathrm{d}}-1}\right)\leqslant 100\%\right)\right]\\ \quad N_{\mathrm{d}}=N_{\mathrm{d}}-1\end{array}\right.$$

Finally, it is worth noting that the simulation/expert system integration is twofold. In fact, simulation provides the ES with some of its required inputs during SESA application. Also, extensive simulation series were carried out in order to acquire ES knowledge in the approach developing phase. This mainly helped choosing the adequate performance measures [6,20] and refining the problem resolution strategy [6].

3.2. General assumptions

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 only on machine and labor sizing problem of a MS of the job shop type. This type of MS is said to be functional-layout-based. In such a layout, functionally similar machines are grouped into departments where all machines are supposed to be operationally identical. In addition, all material handling and setup tasks within a department are performed by a member of an operator set assigned to the same department. All operators among this set are functionally equivalent and interchangeable. Also, all products are transported and manufactured by batches of a constant size. Finally, the material handling system is bi-directional and the distance between machines of the same department is negligible compared to the average inter departmental distance.

3.3. Performance measures

3.3.1. Main performance measures

The main objective of a large number of simulation-based sizing studies is either maximizing the system throughput or minimizing the amount of work in progress. Some other studies focused on minimizing the inventory cost or the global cost. Unfortunately, in practical applications, it is particularly hard to establish a realistic cost function [1]. Besides, in a competitive market-pull context characterizing MSs belonging to the job shop category, it is common to consider the extent of compliance with due dates (DDs) as a main objective. In fact, minimizing tardiness indirectly yields to minimizing the delay penalties whereas storage costs minimization could be accomplished through earliness minimization. Furthermore, in order to avoid excessive investment costs, all resources should be fully utilized.

Consequently, the present study mainly targets the minimization of tardiness while earliness minimization is considered as a secondary objective since the former is usually considered as a more critical problem. Moreover, while trying to attain both objectives, all resources are subjected to minimal and maximal utilization rate constraints (UR_{M}: Machine utilization rate and UR_{L}: Labor utilization rate). 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 tardy (early) batches. Extensive simulations, carried out in various contexts, showed that MT and ME are by far more informative of the MS state [20]. Also, it is worth noting that each MO due date 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.

3.3.2. Performance measures for machine sizing

The key issue in machine department sizing is to determine a potential "bottleneck" department, i.e.: a department suffering from machine shortage. The average number of batches waiting in machine queues (nw_{M}) is used here as a relative indicator of the lack of machines. In addition, if two departments have practically the same average number of batches waiting in machine queues, the average waiting time of these batches in machine queues (wt_{M}) is used as tiebreaker. Finally a machine excess within a department is naturally diagnosed by a very low UR_{M}.

3.3.3. Performance measures for labor sizing

If manual work (MW) is required and all the department associated operators are busy, the routed batch should wait at the MW station queue. So, even without a necessarily high UR_{L}, the average number of batches waiting at the MW queues (nw_{L}) expresses the extent of labor shortage. In addition, as for machines, the average waiting time at MW queues (wt_{L}) can be used as tiebreaker. Finally, labor excess within a department is based on the UR_{L}.

3.3.4. Steady state performance measure

Finally, and for the sake of statistic reliability of the simulation results, all results are collected in the steady state detected by the stabilization of the overall system throughput.

4. Manufacturing system modeling for simulation

The production of the typical MO pattern by the MS being sized is modelled for simulation using the commercial tool Arena [21]. The model comprises three main components discussed in the following subsections (see Fig. 2).

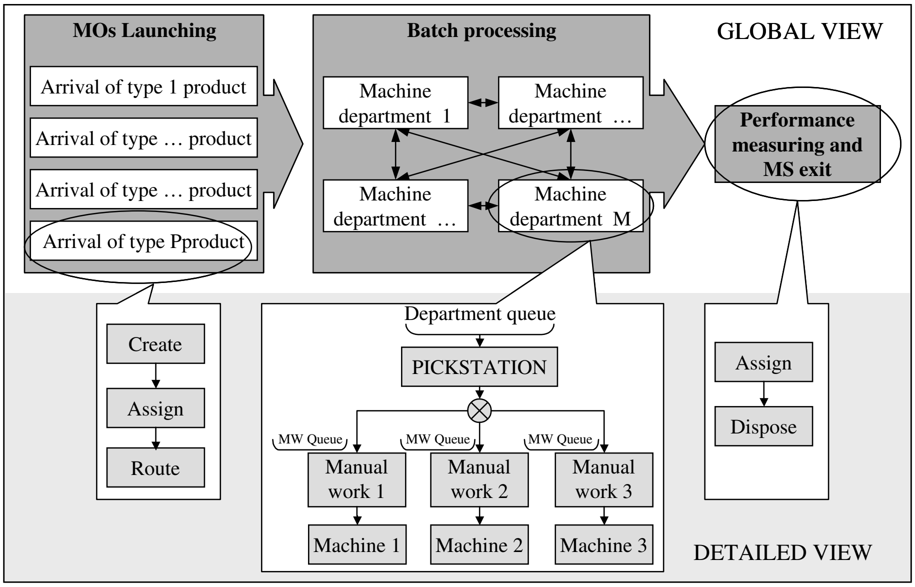

Fig. 2. MS simulation model.

4.1. MOs launching

Product batches are created by a special module permitting to define their size and their arrival frequency following an appropriate statistical rule. Each product type has its own "create" module. Then, operational attributes are assigned to the created batches. These attributes are mainly the product type, the processing and setup times 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.

4.2. Batch processing

4.2.1. Batch routing

When a batch enters a machine department, it waits in the first-in-first-out-governed queue until a machine becomes available. This is done using the "hold" module. Also, before manufacturing a part on a machine, it should be manually loaded and the machine may need a setup operation requiring operator assistance if it was previously set to a different part type. If more than one machine is available, the one having processed the minimum number of batches is picked in order to balance the usage rates among the department machines. The selection is performed by the "pickstation" module.

4.2.2. Manual work

A labor "resource set" dedicated to the loading and setup manual tasks is associated to each machine department. The variable capacity of this resource set corresponds to the number of operators associated with the machine department. Hence, before entering the machine "process" module, every batch should go through the MW "process" module. Since all operators are considered equivalent, this module seizes any available resource among the labor "resource set" for the time period of the corresponding tasks. The associated machine "resource" is also seized during this same time period (see Table 2). However, if all operators are busy, the routed batch should wait at the MW queue.

4.2.3. Processing on machine

As soon as the MW is achieved, the processed batch enters the machine "process" module (see Table 2). This module seizes its corresponding machine "resource" for a time period corresponding to the processing

Table 2
Machine and manual work "process" modules

	"Process" modules	
	Machine	Manual work
Seized resources	One machine resource	One resource from the MW set + One machine resource
Type	Seize/delay/release	Seize/delay/release
Time period	Processing time	Loading time + setup time (if needed)

time. The seized machine resource is subsequently released and becomes eligible to be seized by another job. Finally, depending on its routing, the processed batch is routed either to the next department or to the system exit.

4.3. Performance measuring and system exit

Lastly, before a batch leaves the MS, it should go through an "assign" module dedicated to compute and update the various performance measures presented in Section 3.3.

5. Expert system

5.1. General description

The ES shell Kappa-PC [22] is utilized to develop an ES for manufacturing resource sizing (ESMRS). This decision aiding tool is an object oriented rule-based ES. The main objects classes of this knowledge based system are: *optimization objective, performance measures, machine departments, performance limits and optimization history*. Each of these objects is characterized by a set of private data called *attributes* and a set of intrinsic functions called *methods*. The objects are organized hierarchically into classes and sub-classes corresponding to the different components of the problem. For instance, 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. Except for labor resources, introduced in the present work, the key objects and their attributes are depicted in Chtourou et al. [5]. Besides, the global ES "know-how" is stored in the rule base comprising inference rules of the form: "IF [*condition*] THEN [*action*]". These rules are grouped into several "packs", each representing one of the key functions of the ES. Hence, the ES inference engine exploits both static and dynamic knowledge in order to generate recommendations for MS resource modifications using a deductive reasoning mechanism known as forward chaining. For more details on the structure of ESMRS, the reader is referred to Chtourou et al. [5].

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 current stage as explained in Section 5.2. Finally, all simulation results as well as user prescribed performance limits are introduced via the ES user interface that also serves to communicate recommendations about resource quantity adjustment.

5.2. Reasoning mechanism

5.2.1. Dual resource sizing

Two alternatives are possible for sizing both machines and operators. The first consists in resolving machine lack/surplus problems without labor constraints before tackling labor requirement problem in a second stage. As for the second, both machine and labor lack/surplus problems are resolved concurrently. Both options were experimentally studied by Masmoudi et al. [6]. The authors concluded that the double stage strategy is simpler and more stable. In fact, the first option involves much less interaction between machine and operator levels than the second. The same study served to acquire knowledge about the effects of labor constraints on the solution of the machine sizing problem. In the present work, the double stage strategy is adopted and the acquired knowledge is exploited to build rules for the labor sizing stage.

5.2.2. Machine sizing

The first task in stage 1 is to verify that the MS performance is not significantly deteriorated by the last cycle recommendation (see Fig. 3). If this test is positive, a new cycle starts by updating the best solution if a significant improvement is observed. Else, a new iteration of the previous cycle will take place by trying to recuperate non explored recommendations from the previous cycle. Next, the ES diagnoses all tardiness problems before checking potential violations of the utilization rate constraints. The earliness minimization objective comes then in the third importance rank. This ranking also governs the first test. So, for instance, if a significant improvement of the utilization rates implies a significant increasing of tardiness, the corresponding recommendation is simply cancelled. In this case, the ES recuperates and then proposes the next element from the last cycle recommendation list. Once all problems are diagnosed, the ES tries to set up the list of corresponding feasible recommendations. Such recommendations should ensure the feasibility of all MOs without leading to a previously obtained solution. Then, the ES ranks the feasible recommendations according to the severity of

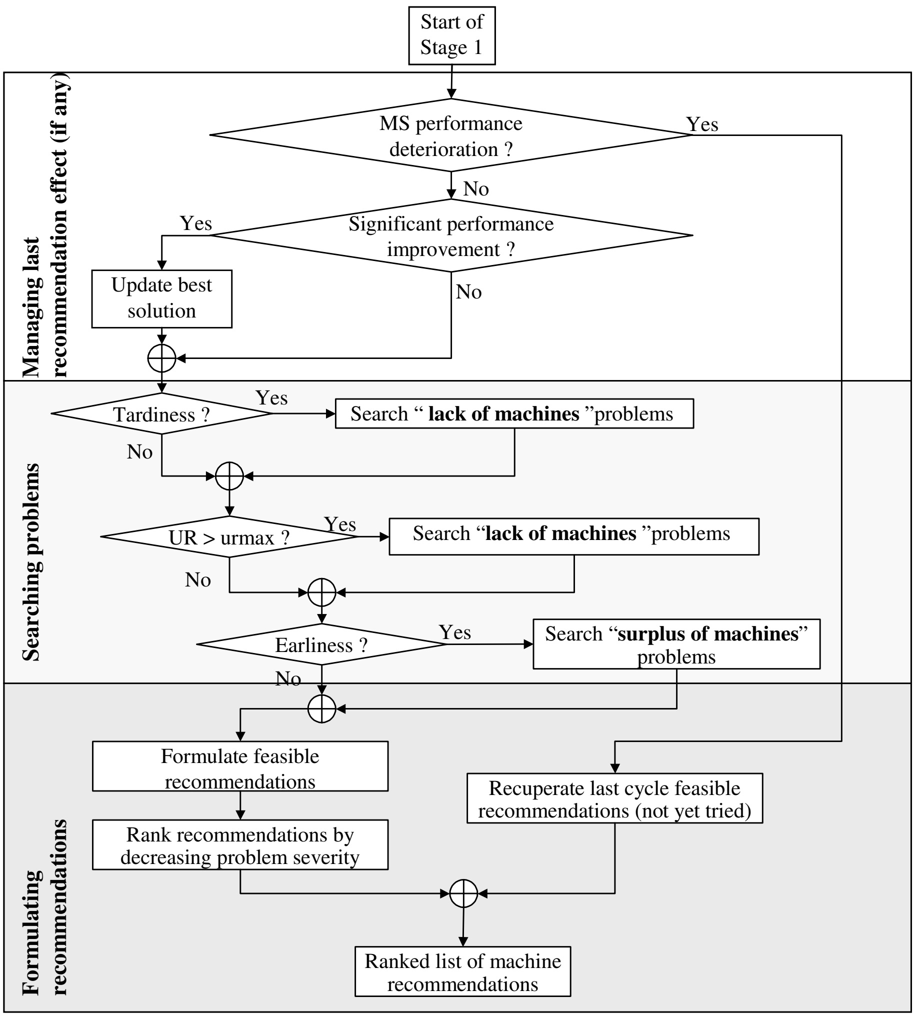

Fig. 3. *Stage 1*: Machine sizing.

the related problems. Thus, a "lack of machine" problem is considered as more critical than a surplus situation. In addition, "lack of machine" problem solutions are ranked by decreasing nw_{M} order of their corresponding departments whereas the more severe "surplus of machine" problem corresponds to the department with the lowest UR_{M}. The absence of feasible recommendations means the end of the first stage. At this point, the adjustment procedure for the initial labor solution (see Section 3.1) is performed before launching the second stage.

5.2.3. Labor sizing

The reasoning mechanism of the second stage is very similar to the one of the first in the sense that it comprises the same three main tasks (see Fig. 4). However, the maximum and minimum limits of the operator utilization rates do not apply. Hence, after managing the previous cycle modification effects in a manner similar to the one of the first stage, the ES first tries to diagnose all labor-lack-related tardiness problems. Then, the ES tackles earliness problems by trying to identify departments with labor surplus. To identify such problems, Masmoudi et al. [6] carried out a series of "learning" simulations in order to acquire knowledge about the effect of labor levels on the MS performance in various situations. The obtained results suggest the formulation of the following labor excess diagnosis rule:

$$\textbf{IF}\{[(UR_{\mathrm{L}} * N)/(N-1)]\ \text{AND}[N > 1]\ \text{is low}\}\ \textbf{THEN}\ \{\text{The number of operators } N \text{ is oversized}\}$$

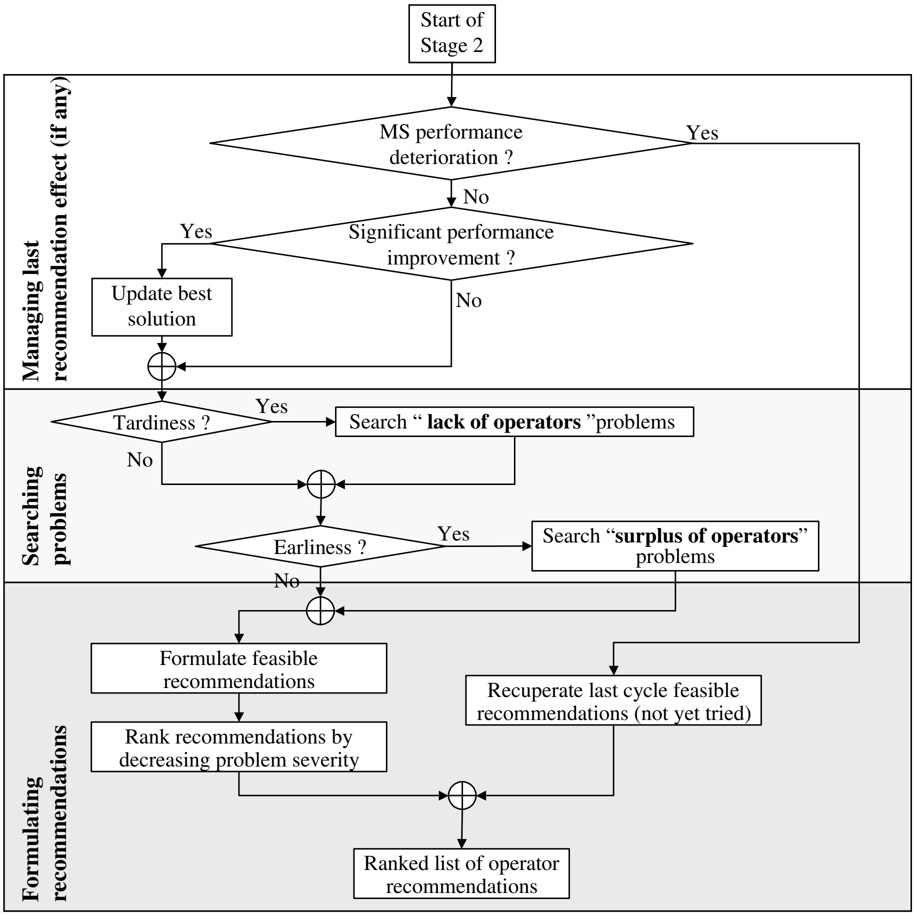

Fig. 4. *Stage 2*: Labor sizing.

From another perspective, a lack of labor resources seemed to be diagnosable by a high value of nw_L without a necessarily high UR_L. Once all problems are diagnosed, the ES tries to establish the list of corresponding feasible recommendations in an analogous manner to the one of the first stage.

6. Illustrative example

In this section we illustrate the application of the enhanced approach through the same example treated by Chtourou et al. [5]. Nevertheless, unlike the latter study, both machine and labor quantities can here be determined. The MS to be sized is a job shop composed of five machine departments (M1 to M5). The typical demand pattern consists of single product MOs launched following a Poisson's law (as in Newman and Maffei [23]) and with a batch size (BS). In addition, each manufactured product type (P1 to P3) is characterized by a specific routing resulting in a specific total work content (TWK) obtained by summing up the processing times (PTs) on all workstations and the needed transport times. The setup times (STs), governed by a triangular law [23], are not included in the TWK since this parameter is calculated for the most favorable situation where the machines are already set for the same product. For each MO, the DD is set to be the product of factor expressing its tightness by its corresponding TWK. Also, a significance threshold (S%) is taken here as 3% of the aggregate DD (approximately 10 000 min). This threshold is used to judge the significance of performance measures improvement or deterioration. Finally, maximum and minimum allowed utilization rates for the machine departments are respectively 90% and 20%. The main characteristics of the MS and the demand pattern are recapitulated in Table 3.

The SESA approach was applied with the following initial MS $[1|1]_1$ $[2|2]_2$ $[3|3]_3$ $[4|4]_4$ $[5|5]_5$. Using this notation, resources of each departments (1 to 5) are in square brackets [ ] which include respectively the machine quantity and the operator quantity separated by "|" whereas the department index is in subscript. The SESA "Simulation – ES optimization" cycles are performed, in a first stage, to optimize MS machine quantities. Totally, 13 cycles were necessary to reach a non improvable performance of MS in terms of machine number: the best solution at this level was $[5|5]_1$ $[4|4]_2$ $[5|5]_3$ $[7|7]_4$ $[5|5]_5$. The modifications applied in the various cycles of optimization of this application first stage are summarized in Table 4.

The intermediary proportionality rule was applied to suggest initial MS operator quantities to start SESA second stage: $[5|1]_1$ $[4|1]_2$ $[5|1]_3$ $[7|1]_4$ $[5|1]_5$. Four other cycles were necessary to reach the definitive solution $[5|1]_1$ $[4|1]_2$ $[5|2]_3$ $[7|2]_4$ $[5|1]_5$. (See Table 5).

Hence, by including operator sizing into SESA, the assumption that the number of operators being equal to the number of machines is dropped. And so, it is shown that the required number of operators is much lower than the one suggested by the dropped assumption, without any significant performance deterioration (see Fig. 5).

Table 3
Input for the illustrative example

Product type	Manufacturing data				Demand data	
	Routing (Department)	PT (min)	ST (min)	TWK (min)	BS	Inter-arrival law (min)
P1	M3	20	Triangular (115,120,125)	790	0	Poisson's (120)
	M1	25	Triangular (20,25,30)			
	M2	30	Triangular (25,30,35)			
P2	M2	5	Triangular (25,30,35)	840	20	Poisson's (120)
	M3	15	Triangular (95,100,105)			
	M4	20	Triangular (100,105,110)			
P3	M1	10	Triangular (20,25,30)	1240	30	Poisson's (120)
	M4	10	Triangular (145,150,155)			
	M5	20	Triangular (70,75,80)			

Table 4
Results of first stage application

Simulation results													ES results						
Cycle	*nw*					*ur*					MT	ME	Last proposed solution		Quantities of resources				
	M1	M2	M3	M4	M5	M1	M2	M3	M4	M5			Accepted	Best yet	M1|opr1	M2|opr2	M3|opr3	M4|opr4	M5|opr5
Initial solution															1|1	2|2	3|3	4|4	5|5
1	566	0	311	0	0	100	52	100	61	24	27 298	0	Yes	Yes	**2|2**	2|2	3|3	4|4	5|5
2	299	0	282	0	0	100	78	100	88	50	18 660	115	Yes	Yes	**3|3**	2|2	3|3	4|4	5|5
3	104	77	200	44	0	100	100	100	100	64	12 118	691	Yes	Yes	3|3	2|2	**4|4**	4|4	5|5
4	188	143	0	68	0	100	100	91	100	55	11 464	378	Yes	Yes	**4|4**	2|2	4|4	4|4	5|5
5	0	264	0	71	0	95	100	81	100	70	8 700	2 072	Yes	Yes	4|4	**3|3**	4|4	4|4	5|5
6	0	0	48	213	0	93	89	100	100	59	5 431	1 695	Yes	Yes	4|4	3|3	4|4	**5|5**	5|5
7	0	0	48	62	0	93	86	100	100	73	674	3 813	Yes	Yes	4|4	3|3	4|4	**6|6**	5|5
8	0	0	45	0	0	94	90	100	88	77	0	6 298	Yes	Yes	4|4	3|3	**5|5**	6|6	5|5
9	0	0	0	0	0	94	95	82	91	77	0	8 447	Yes	No	4|4	**4|4**	5|5	6|6	5|5
10	0	0	0	0	0	93	69	83	93	77	0	8 451	Yes	No	4|4	4|4	5|5	**7|7**	5|5
11	0	0	0	0	0	94	69	83	77	77	0	8 498	Yes	No	**5|5**	4|4	5|5	7|7	5|5
12	0	0	0	0	0	75	69	83	76	77	0	8510	Yes	Yes	5|5	**3|3**	5|5	7|7	5|5
13	0	0	0	0	0	77	95	81	76	76	0	8 479	No	No	5|5	4|4	5|5	**6|6**	5|5
13	0	0	0	0	0	75	68	83	91	77	0	8 498	No	No	5|5	4|4	5|5	7|7	**4|4**
13	0	0	0	0	0	74	68	83	77	100	0	8 462	No	No	5|5	4|4	**4|4**	7|7	5|5
13	0	0	0	0	0	75	63	100	76	77	0	5 613	No	No	*No solution: End of the stage 1*				

Table 5
Results of the second stage application

Simulation results													ES results						
Cycle	*nw*					*ur*					MT	ME	Last proposed solution		Quantities of resources				
	Opr 1	Opr 2	Opr 3	Opr 4	Opr 5	Opr 1	Opr 2	Opr 3	Opr 4	Opr 5			Accepted	Best yet	M1|opr1	M2|opr2	M3|opr3	M4|opr4	M5|opr5
Initial solution (suggested by the proportionality rule)															5|1	4|1	5|1	7|1	5|1
1	0	0	54	0	0	10	13	99	63	0	15176	5348	Yes	Yes	5|1	4|1	5|**2**	7|1	5|1
2	0	0	0	36	0	18	17	43	98	0	13808	3481	Yes	Yes	5|1	4|1	5|2	7|**2**	5|1
3	0	0	0	0	0	17	16	49	41	0	0	8486	Yes	Yes	5|1	4|1	5|**1**	7|2	5|1
4	0	0	59	0	0	13	15	97	27	0	15909	5414	No	No	*No solution: End of the approach*				

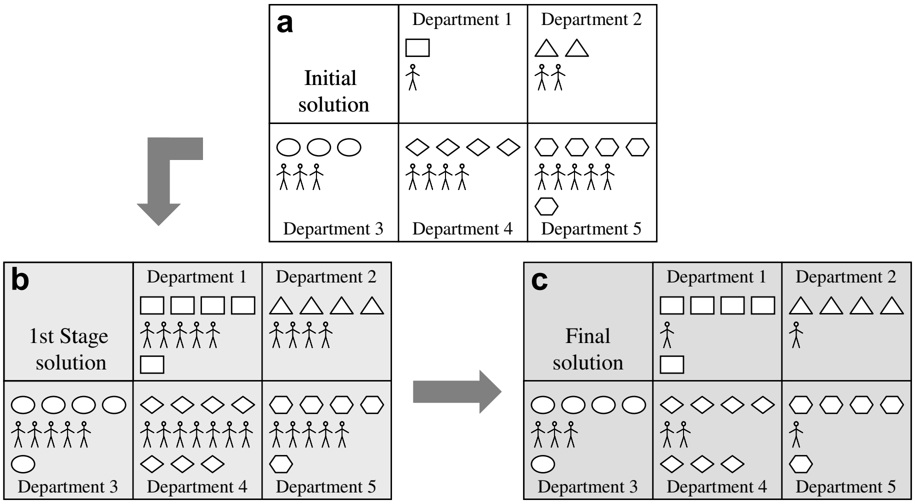

Fig. 5. A glance at the solution evolution.

7. Conclusion

This study presents an enhanced version of the SESA coupling an ES and a simulation tool for MS labor and machine sizing. This version of the approach uses performance measures that are adapted to the due date characterized "make to order" production context. It also allows for considering the stochastic aspect governing several manufacturing aspects. The approach application on an illustrative example showed the potential benefits of the approach enhancements through the enrichment of both the simulation model and the ES reasoning mechanism.

Finally, many aspects of the approach are currently being developed. The first task is the enlargement of the domain of application and consequently, enrichment of the simulation model by considering resource reliability and routing flexibility. This should increase the chance of the approach to be successfully applied and validated on real cases. Also, a thorough investigation of the approach robustness and applicability in various scenarios is planned.

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