A Bi-objective Based Measure for the Scalability of Reconfigurable Manufacturing Systems

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Abstract. The reconfigurable manufacturing systems aim to efficiently respond to demand changes. One of the key characteristics of these systems is the scalability, i.e. the ability to modify the volume of the throughput in order to fit to the demand variability. The design of the RMS has a high impact on its scalability. In the literature, there are only few indicators to evaluate the scalability of a system and most of them are a posteriori measures. In this article, we propose a new measure to assess the scalability since the design phase of the RMS. We present experimental results on state-of-the-art instances to validate our approach. They show that the proposed measure evaluates accurately the scalability.

Keywords: Scalability · Reconfigurable manufacturing systems · Multi-objective indicator.

1 Introduction

In a context of high volatility of market conditions and increased customization leading to smaller batches, manufacturing companies have to react quickly and efficiently to changes in order to remain competitive. Reconfigurable Manufacturing Systems (RMS) have been introduced in [10] to answer to this need of adaptability. Basically the main purpose of RMS is to manage shorter product lifecycles while keeping longer production system lifecycles.

RMS are production systems composed of serial stages with identical parallel resources, which can be automated (for example Computer Numerical Control (CNC) or Reconfigurable Manufacturing Tools (RMT)), or other resources such as workers or cobots. A gantry and a conveyor are generally used to move the products in this grid of stations [9]. A RMS layout is schematized in Figure 1.

The efficiency of RMS relies on six key features : modularity (ability to reuse machines and tools), integrability (ability to rapidly and efficiently connect new modules), diagnosability (ability to identify automatically a problem in the production system), convertibility (ability to change the system for new products), customization (ability to produce different parts in a family) and scalability (ability to adapt the volume of production). The four first ones are

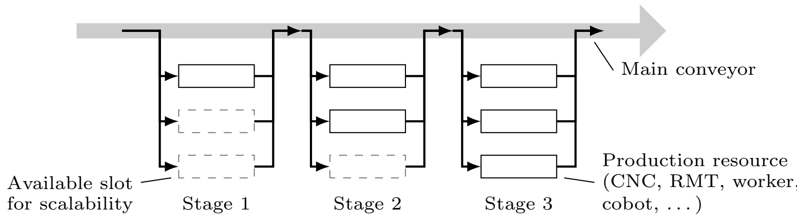

Fig. 1. RMS layout as seen by [9]

mainly related to technological issues while the two last ones are related to organizational issues. [11] states that scalability might be the most important feature to deal with the uncertain demand or ramp-up phase. This adaptation can be achieved by two levers, either (a) adding or removing parallel resources on the stations, or (b) processing a full reconfiguration of the system by changing the tools used in RMT or CNC machines[15]. A scalable system of good quality must be able to adapt quickly, incrementally (in small steps) and cost-effectively in order to provide at any time the exact capacity needed. In this paper, we focus on the first lever, which is the one allowing for the shorter and less expensive reconfiguration times, and we propose a new indicator to assess the scalability of an RMS, integrating these three aspects, at a strategic level and independantly of the initial state of the system.

The remaining of the paper is organized as follows: Section 2 presents the related literature, the proposed scalability measure is explained in Section 3 and experimental results are analyzed in Section 4. Section 5 concludes this paper.

2 Related literature

The articles dealing with scalability of RMS can be separated in two categories, according to the decision level : operational or strategical.

The first category contains works dealing with the planning of the configurations. They focus on how to use the scalability of RMS to adjust production throughput over time to face the evolution of demand. [3, 4] present a dynamic method to assess different reconfiguration policies on various scenarios of demand evolution. This method deals with each reconfiguration independently. [19] presents a heuristic method to minimize the number of machines required for successive reconfigurations. An extension of this method has been presented in [11], integrating buffers in RMS. The scalability level of different configurations of RMS are evaluated a posteriori with the production throughput gain when adding a given number of machines and rebalancing the line. Since the method is a heuristic, it is difficult to evaluate if the throughput comes from the scalability level of configurations or from the performance the optimization method. Based on the experimental results obtained, the authors stated that a lower number of stages leads to higher throughput and gain, mainly because it leads to a more reliable system. [5] has also used simulation to study the advantages of using RMS when dealing with unreliable production systems. [6] proposed a new approach for production planning to realize capacity scalability and functionality changes in planning processes. A prototypical application is developed to prove the applicability of their method. [8] presents a simulation-based method to optimize the production planning of RMS taking into account the variations of demand. [7] uses Petri nets to model an auto-adaptive RMS based on multi-agents to adjust production capacity.

The second category of studies considers the scalability of the RMS at the design phase. [10] and [18] studied the impact of different system configurations on throughput and scalability. [17] questioned the link between the balancing of the production systems and its productivity and scalability. They highlighted that unbalanced RMS can generate smaller steps of capacity changes. More recently, [13] proposed a classification of the main root causes leading to convertibility and scalability. Also, whereas RMS have been initially introduced for discrete manufacturing, [1] proposed to extend the definition of scalability to integrate process manufacturing and to calculate the average wasted capacity for a given curve of demand. In [19], a metric based on the smallest possible incremental capacity change is presented to evaluate a priori scalability on the first reconfiguration. However this metric is dependent on the current state of the system and does not allow to take into account the subsequent reconfigurations. Indeed, [15] states there is a need for new performance measures of scalability.

Finally, some works try to integrate the two decision level. In [12], the problem of design multi-product and scalable RMS for multiple production periods is addressed, minimizing design and reconfiguration costs while fulfilling demand. The authors presented two approaches: a up- and downgrading method based on approximate demand in each period; and RMT selections and reconfigurations based on long-term demand estimations. A similar problem of design and reconfiguration planning was considered in [2] where the authors use the scalability of a mono-product RMS to minimize the energy cost.

3 Hypervolume based indicator for scalability

In this study, we consider reconfigurations based on the same assignment of tasks to the stages. A configuration is thus defined by these two pieces of information: the balancing and the number of resources in each stage, and a reconfiguration consists in varying the number of resources on the stages, e.g. by switching on/off some resources. The cycle time of a stage is the workload (i.e., the sum of the processing time of tasks assigned to it) divided by the number of resources assigned to the stage. The takt time of a configuration is defined by the stage with the highest cycle time. Obviously, the only interesting configurations are those with the highest productivity for the same number of resources. A set of configurations can be derived for each feasible balancing, i.e. such that each tasks is assigned to one and only one stage, respecting the precedence constraints. For a given balancing, these configurations can be obtained by an iterative method:

starting with one resource on each stage and gradually adding a resource in the bottleneck stages (i.e. the stages with the highest cycle time).

Knowing the whole set of available configurations, we can sort them by increasing number of resources and calculate the smallest capacity increment starting from each configuration by looking at the resources gap with the next configuration. We can thus obtain the average value of this stability measure among all the configurations, however it would not take into account some important features such as the available range of productivity or the efficiency of configurations. Actually, a scalable balancing should ideally provide a set of highly efficient configurations (i.e., with few idle times) covering a large range of possible market demands with a small increment between them. These characteristics are very similar to the ones sought from a set of trade-offs in the fields of multi-objective optimization and we can thus use the same metrics. Here, we will focus on one of the most used multi-objective metric which is the hypervolume [20]. For an optimization problem with multiple objectives to minimize, the hypervolume is the area above the set of points to evaluate and below a reference point (point such that it is not possible to have highest value along any objective). It is denote $\mathcal{H}$ in the following.

Two objectives are considered in our scalability measure: the takt time (to assess the productivity of the configurations) and the number of resources (to evaluate their cost). These two criteria are to be minimized. A reference point for the hypervolume computation can easily be determined since a configuration cannot have a takt time strictly greater than the sum of the processing times and the number of resources in bounded (otherwise there would be an infinity of configurations derived from a balancing).

To evaluate the quality of a set of configurations, we compare the objective values obtained for the specific set associated with a balancing (denoted by F_a), with the best possible values, i.e. with the whole set of feasible balancings and all derived configurations (F_r, it is a Pareto front [14]):

$$HV = 1 - \frac{\mathcal{H}(F_a)}{\mathcal{H}(F_r)}.$$

HV is in [0,1] and a low value indicates that the configurations derived from the considered balancing are close from the best possible values (F_r) and thus indicates that this set of configurations is of good quality.

4 Experimental results

We conducted experiments to evaluate the proposed indicator and to compare it with, on one hand, some classical line balancing indicators (takt time, number of stages, idle time and smoothness index computed on the configuration with one resource per station) and on the other hand the average scalability value from [19] on all configurations. This scalability indicator for a configuration is either the smallest incremental capacity in percentage (i.e. the number of bottleneck stages over the total number of resources in the system) if it is possible to add resources in all bottleneck stations, or the number of stages otherwise (corresponding to the creation of a whole new line).

For an instance, this comparison is done for all feasible balancings, obtained by a total enumeration under the following assumptions:

- There cannot be more than three resources per stage.
- The total number of resources for a configuration cannot exceed 50% of the number of tasks.
- At most 50% of the tasks can be assigned to the same stage.

The 10 smallest instances from [16] are used as a benchmark. We limited the time for the enumeration to 5 minutes, on a computer with an Intel Core i7, with a 2.60 GHz processor with 16 GB of RAM. Under these conditions, only the 5 smallest instances completed the process under the time limit. For the other, we gradually reduced the number of operations, following a random order, until the resulting instance finished the process under the time limit. Table 1 summarizes the initial number of operations of the considered instances and the size of the instances solved by our process.

Instance name	Size
Mertens	7
Bowman8	8
Jaeschke	9
Jackson	11
Mansoor	11

Instance name	Original size	Reduced size
Mitchell	21	14
Roszieg	25	13
Heskia	28	11
Buxey	29	12
Sawyer30	30	11

Table 1. Description of the benchmark instances size (number of tasks). The table on the left are the instances for which the execution finished within the time limit and the one on the right contains the instances that needed to be reduced for the experiments.

Table 2 shows the correlation between the classical line balancing indicators and both the average scalability indicator from [19] and the proposed hypervolume metric HV. Since all indicators are to be minimized, the high score indicates a strong correlation. The table shows that neither the average scalability nor the HV indicator are correlated with the classical line balancing measures, except with the number of stages. The strong correlation with the number of stages can be explained by the fact that a low number of stages most likely allows to derive more configurations within the limit of number of resources per stage or in the system. The HV indicator is highly impacted by the number of configurations in the set. When computing the average scalability indicator, there is always a configuration for which the indicator corresponds to the creation of a new line (thus with a particularly high value) which has less impact if the set of configurations is large. However, the number stages alone does not give any guaranty on the productivity of the configurations. It is also interesting to note that the average scalability is almost unrelated to the smoothness index which is the most usual indicator used to assess if a solution is well-balanced. Thus this table shows that the classical line balancing indicators cannot be used to evaluate the scalability of a RMS.

	takt time	nb of stages	idle time	smoothness
avgScalability	-0.372	0.951	0.237	0.093
HV(F^a)	-0.220	0.981	0.432	0.292

Table 2. Correlation of the classical SALBP indicators with the scalability indicators

Instance	avg Scalability
Mertens	0.920
Bowman8	0.959
Jaeschke	0.953
Jackson	0.927
Mansoor	0.954

Instance	avg Scalability
Mitchell	0.895
Roszieg	0.922
Heskia	0.946
Buxey	0.922
Sawyer30	0.942

Table 3. Correlation of the hypervolume with the average scalability from [19]

Table 3 shows a strong correlation between the average scalability indicator from [19] and the proposed hypervolume metric HV, for each instance of the benchmark, with low variability. This means that on most of the balancings, the two measures agree of the assessment of the scalability, but not on all of them. Indeed, for a balancing with a high number of configurations derived, the average scalability indicator will be high, but the HV indicator can be quite low if the takt time of these configurations is high (when the stages are unbalanced, the productivity is then low).

Instance	min HV	avgHV
Mertens	0.0%	0.3%
Bowman8	3.1%	59.9%
Jaeschke	3.6%	48.3%
Jackson	6.6%	61.7%
Mansoor	7.4%	61.9%

Instance	min HV	avgHV
Mitchell	4.4%	72.3%
Roszieg	4.8%	72.4%
Heskia	5.8%	70.6%
Buxey	8.4%	72.0%
Sawyer30	5.8%	71.1%
Average on all instances	4.99%	59.05%

Table 4. Minimum and average value of the hypervolume metric among all balancings

Finally, Table 4 shows the minimum and average values of the hypervolume indicator HV among all the balancings for each instance. Since the indicator HV is based on the ratio of the hypervolume on the set of configurations derived from the same balancing and the set of best possible values, the minimum HV evaluates the quality of the optimal balancing (according to the HV metric) with respect to a case where every reconfiguration would be possible. Here we have an average gap of 5% which corresponds to the cost of the assumption to only consider sets of configurations based on the same balancing. This cost seems really low by comparison with the additional costs of reconfiguration times associated with a change of tools. The average HV evaluates the quality of a random balancing which is significantly higher (nearly 60%). This highlights the potential gains of optimizing this indicator during the design phase.

5 Conclusion

Scalability is a one of the main characteristics of RMS but its evaluation at the design step has not received a lot of attention. Only two works have considered this issue: (a) [19] has defined a measure based on the smallest increment required to increase the capacity starting from for a given configuration, and (b) [13] has tried to identify the core characteristics leading to the scalability. In this paper, we propose a new measure based on a classical multi-objective metric to assess the scalability level of a balancing by taking into account all the configurations which can be achieved.

The preliminary results show that this approach can be viewed as an extension of the smallest increment measure which is not dependent on a specific initial state. It also reveals that the usual line balancing criteria are mainly unrelated with the scalability, enhancing the need for dedicated metrics which could be used to optimize the scalability at the design step. This conclusion fits with the statement of [17] on the possibility to have a good scalability level in some unbalanced RMS. It is also interesting to note that, similarly to the conclusions reported in [11], in our setting a lower number of stages is strongly and positively correlated with the scalability even without taking the reliability into account.

A first perspective of this work would be to use the proposed measure to characterize what makes a system scalable. In addition, this work focuses on only one of the RMS characteristics. Even if a priori the different characteristics seem to be independant, it would be interesting to study their interaction. Finally, the development of methods to design RMSs optimizing their scalability together with classical performance measures would be needed.

References

1. Accorsi, R., Bortolini, M., Galizia, F.G., Gualano, F., Oliani, M.: Scalability analysis in industry 4.0 manufacturing. In: Scholz, S., Howlett, R., Setchi, R. (eds.) Sustainable Design and Manufacturing 2020. Smart Innovation, Systems and Technologies, vol. 200, pp. 161–171. Springer, Singapore (2021)
2. Cerqueus, A., Gianessi, P., Lamy, D., Delorme, X.: Balancing and configuration planning of rms to minimize energy cost. In: Lalic, B., Majstorovic, V., Marjanovic, U., von Cieminski, G., Romero, D. (eds.) Advances in Production Management Systems. Towards Smart and Digital Manufacturing. APMS 2020. IFIP Advances in Information and Communication Technology, vol. 592, pp. 518–526. Springer, Cham (2020)
3. Deif, A.M., EIMaraghy, W.H.: A control approach to explore the dynamics of capacity scalability in reconfigurable manufacturing systems. Journal of Manufacturing System **25**(1), 12 – 24 (2006)

4. Deif, A.M., ElMaraghy, H.A.: Assessing capacity scalability policies in rms using system dynamics. International Journal of Flexible Manufacturing Systems **19**, 128 – 150 (2007)
5. Gola, A., Pastuszak, Z., Relich, M., Sobaszek, L., Szwarc, E.: Scalability analysis of selected structures of a reconfigurable manufacturing system taking into account a reduction in machine tools reliability. Eksploatacja i Niezawodnosc Maintenance and Reliability **23**(2), 242–252 (2021)
6. Hees, A., Schutte, C.S., Reinhart, G.: A production planning system to continuously integrate the characteristics of reconfigurable manufacturing systems. Production Engineering **11**(4-5), 511–521 (2017)
7. Hsieh, F.S.: Design of scalable agent-based reconfigurable manufacturing systems with petri nets. International Journal of Computer Integrated Manufacturing **31**(8), 748 – 759 (2018)
8. Hu, Y., Guan, Y., Han, J., Wen, J.: Joint optimization of production planning and capacity adjustment for assembly system. Procedia CIRP **62**, 193 – 198 (2017)
9. Koren, Y., Gu, X., Guo, W.: Reconfigurable manufacturing systems: Principles, design, and future trends. Frontiers of Mechanical Engineering **13**(2), 121 – 136 (2018)
10. Koren, Y., Hu, S.J., Weber, T.W.: Impact of manufacturing system configuration on performance. Annals ofthe CIRP **47**(1), 369 – 372 (1998)
11. Koren, Y., Wang, W., Gu, X.: Value creation through design for scalability of reconfigurable manufacturing systems. International Journal of Production Research **55**(5), 1227 – 1242 (2017)
12. Moghaddam, S.K., Houshmand, M., Saitou, K., Fatahi Valilai, O.: Configuration design of scalable reconfigurable manufacturing systems for part family. International Journal of Production Research **58**(10), 2974–2996 (2020)
13. Napoleone, A., Andersen, A., Pozzetti, A., Macchi, M.: Reconfigurable manufacturing: A classification of elements enabling convertibility and scalability. In: Ameri, F., Stecke, K., von Cieminski, G., Kiritsis, D. (eds.) Advances in Production Management Systems. Production Management for the Factory of the Future. APMS 2019. IFIP Advances in Information and Communication Technology, vol. 566, pp. 349–356. Springer, Cham (2019)
14. Pareto, V.: Manuel d'économie politique. F. Rouge, Lausanne (1896)
15. Putnik, G., Sluga, A., ElMaraghy, H., Teti, R., Koren, Y., Tolio, T., Hon, B.: Scalability in manufacturing systems design and operation: State-of-the-art and future developments roadmap. CIRP Annals - Manufacturing Technology **62**, 751 – 774 (2013)
16. Scholl, A.: Balancing and Sequencing of Assembly Lines. Contributions to Management Science, Physica-Verlag HD (1999)
17. Son, S.Y., Olsen, T.L., Yip-Hoi, D.: An approach to scalability and line balancing for reconfigurable manufacturing systems. Integrated Manufacturing Systems **12**(7), 500 – 511 (2001)
18. Spicer, P., Koren, Y., Shpitalni, M., Yip-Hoi, D.: Design principles for machining system configurations. CIRP Annals **51**(1), 275 – 280 (2002)
19. Wang, W., Koren, Y.: Scalability planning for reconfigurable manufacturing systems. Journal of Manufacturing Systems **31**(2), 83 – 91 (2012)
20. Zitzler, E., Thiele, L., Laumanns, M., Fonseca, C.M., da Fonseca, V.G.: Performance assessment of multiobjective optimizers: an analysis and review. IEEE Transactions on Evolutionary Computation **7**(2), 117–132 (2003)