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# Investigating optimal capacity scalability scheduling in a reconfigurable manufacturing system

**Abstract** Responsiveness to dynamic market changes in a cost-effective manner is becoming a key success factor for any manufacturing system in today's global economy. Reconfigurable manufacturing systems (RMSs) have been introduced to react quickly and effectively to such competitive market demands through modular and scalable design of the manufacturing system on the system level, as well as on the machine components' level. This paper investigates how RMSs can manage their capacity scalability on the system level in a cost-effective manner. An approach for modeling capacity scalability is proposed, which, unlike earlier approaches, does not assume that the capacity scalability is simply a function of fixed increments of capacity units. Based on the model, a computer tool that utilizes a genetic algorithm optimization technique is developed. The tool aids the systems' designers in deciding when to reconfigure the system in order to scale the capacity and by how much to scale it in order to meet the market demand in a cost-effective way. The results showed that, in terms of cost, the optimal capacity scalability schedules in an RMS are superior to both the exact demand capacity scalability approach and the approach of supplying all required capacity at the beginning of the planning period, which is adopted by flexible manufacturing systems (FMSs). The results also suggest that the cost-effective implementation of an RMS can be realized through decreasing the cost of reconfiguration of these new systems.

**Keywords** Reconfigurable manufacturing systems · Capacity scalability · Regeneration point and genetic algorithm

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## 1 Introduction

Shorter product life-cycles, unpredictable demand, and customized products have forced manufacturing systems to operate more efficiently in order to adapt to changing requirements. Global competitive situations have led to increasing attention being paid to customer satisfaction, of which responsive and customized services are the key concepts. Traditional manufacturing systems like dedicated machine lines (DMLs) or cellular manufacturing systems (CMSs) cannot cope with these new market characteristics. Even flexible manufacturing systems (FMSs) cannot deal with these new requirements in a cost-effective manner. To meet these modern challenges, reconfigurable manufacturing systems (RMSs) were proposed. RMSs aim at combining the high throughput of a DML with the flexibility of an FMS, maintaining the ability to deal with a variety of products and volumes in a cost-effective manner. This is achieved through rapid change in its structure, as well as its hardware and software components, in order to accommodate rapid adjustment of the exact capacity and functionality needed and when it is needed [1].

Shabaka and ElMaraghy [2] explain the dimensions of the reconfiguration of the manufacturing systems through classifying the reconfiguration process into its physical configuration and logical configuration. Examples of physical configurations include layout configuration, adding or removing of machines, adding or removing of machines' tools or components, and material handling system reconfiguration. Examples of logical configurations include the re-programming of machines, re-planning, re-scheduling, re-routing, and increasing or decreasing shifts or the number of workers. The key characteristics of RMSs are modularity, integrabilty, convertibility, customization, and diagnosability [3].

The previous characteristics enable RMSs to have unfixed capacity and functionality and, thus, they are assumed to be scalable systems. The modular structure of the system components is responsible for the physical scalability, while the modern open architecture controls techniques are the main tool for logical or software scalability. The focus of this paper is on the modeling of the physical capacity scalability in an RMS.

## 2 Capacity scalability problem in manufacturing systems

Capacity scalability is simply the ability to adapt to changing demand. A typical capacity scalability problem addresses when, where, and by how much should the capacity of the manufacturing system be scaled. Before RMSs, the scope of this problem was limited to capacity expansion. With RMSs, on the other hand, capacity scalability addresses the reduction of capacity besides the expansion. Another major difference between both trends is the enabling of an RMS to scale the capacity not only over the system level, but also over the machine level by virtue of its modular and open control structures. The cost of capacity expansion is traditionally justified by the economy of scale of the expanded capacity. In an RMS, it is assumed that capacity scalability is justified by reducing the shortage cost, since capacity is supplied when needed and it reduces the cost of the underutilized capacity, as the exact capacity is available where needed. The latter gives the RMS an advantage over FMSs. The cost-effectiveness of the capacity scalability, together with the functionality scalability, in the RMS is achieved through the concept of economy of scope.

## 3 Review of earlier capacity scalability modeling approaches

Extensive surveys in the literature about classical capacity expansion problem are found in Manne [4], Freidenfelds [5], and Luss [6]. Examples of some approaches to model the capacity in FMSs were proposed by Leachman and Carnon [7], Roundy et al. [8], and Liberopoulos [9].

As for RMSs, Son et al. [10] suggested station paralleling within a stage as a possible approach to scale the capacity within transfer line manufacturing systems, which he referred to as a homogeneous paralleling flow line (HPFL). Asl and Ulsoy [11] presented an approach to capacity scalability modeling in an RMS based on the use of feedback control theory to manage the capacity scalability problem. In their approach, they assumed that the capacity change in the RMS is a quantized set of equal capacity units. Based on this assumption, they developed a deterministic continuous time model of capacity scalability to generate a capacity policy in an RMS at minimum cost. Another approach for capacity management in an RMS with stochastic market demand was also presented by Asl and Ulsoy [12], where an optimal solution for the capacity scalability management based on Markov decision theory was presented. They also considered the time delay between the time that the capacity is ordered and the time at which it is delivered. The optimal policy in their work is presented as optimal boundaries representing the optimal capacity expansion and reduction levels. The effects of change in the cost function parameters and the delay time on the optimal boundaries were presented for a capacity management scenario. Their work is considered as an extension to Rocklin and Kashper's method [13], where they integrated into it their previous dynamic model for capacity scalability.

The previous approaches are the considered as the main approaches for capacity scalability modeling applicable to RMSs. The major shortcoming in the earlier models is the assumption of the capacity scalability as a function of fixed increments of capacity units. In a practical reconfigurable manufacturing environment, this is not the case, since there are different capacity modules on the system level, as well as the machine level, that can be used to scale the capacity. Also, some of these approaches didn't address when exactly to scale the capacity and this is one of the major characteristics of RMSs. These shortcomings are addressed in the proposed model.

This paper, therefore, represents a new approach to model the capacity scalability of an RMS. The focus is on the physical scalability of the systems' capacity rather than considering the logical scaling of their capacity. The objective of the modeling is to develop an optimal capacity schedule which, based on the market demand variation, indicates when to scale the system's capacity and by how much. These schedules are generated by a computer tool that is based on a genetic algorithm optimization technique.

## 4 Proposed capacity scalability model

The proposed model is based on the optimal plant size with arbitrary increasing time paths of demand approach, as presented by Manne and Veinott [14], where the model has been modified and adapted to address the problem of capacity scalability in RMSs. A basic mathematical foundation for the model is one of the concave/convex sets properties that states:

*If C(.) is a concave function on a closed bounded convex set V having finitely many extreme points, then C(.) achieves its minimum on V at an extreme point of V.*

### 4.1 Model assumptions

The following are the assumptions for the model:

1. Time (or capacity planning horizon) is idealized to be consisted of discrete periods 1, 2, ..., $T$.
2. Demand in period $t$ (the difference between demands in periods $t$ and $t-1$) is known as $D_t$, where $D_t \geq 0$ and:

$$\sum_{t=1}^{T} D_t > 0 \tag{1}$$

3. Capacity scalability decision is a set of variables $v_t$, where $t$=1, 2, $T$.
4. $Z_t$ denotes the end of the period of excess capacity. In RMSs, $Z_t$ tends to be zero:

$$Z_t = \sum_{j=1}^{t} \left( v_j - D_t \right) \quad (t = 1,\ 2, \ldots,\ T) \tag{2}$$

A feasible capacity scalability plan or schedule is where:

$$v_t \geq 0 \tag{3}$$

$$Z_0 = 0 \text{ and } Z_T = 0 \tag{4}$$

Let $V$ denote the set of feasible capacity schedules of the RMS. From Eqs. 2, 3, and 4, and since the set of solutions to a finite system of linear equalities and inequalities is a convex set and has finitely many extreme points, it could be said that $V$ is a closed, bounded convex set.

### 4.2 Cost function

The function $C(v)$ represents the cost of having the capacity level $v$. It is time-dependent and is expressed in terms of the present value of costs as of time 1. This cost function is composed of two components, the first reflects the cost of the physical capacity unit that the system will be scaled with, and the second represents the cost associated with this physical scaling or reconfiguration of the system. Thus, the cost for each period $t$ is mainly the cost of having a capacity level $v$ at that time period (which can be scaled up or down) to satisfy the demand. For example, this scaling can be achieved through adding/removing another spindle to a machine, adding/removing a machine, or even adding/removing a group of machines. Thus, the first term of the cost function is an expression of the physical cost of this capacity unit.

On the other hand, the term $CR$ represents other costs of reconfiguration that is associated with this scaling, and basically includes other related cost parameters, such as the cost of downtime to rescale the system or to ramp up the new configuration with the new capacity, the labor cost involved and the effort required for that reconfiguration or scaling. It is important to note that the term $CR$ varies based on the level of reconfiguration required. In this paper, for simplicity, this term is expressed as a linear function that is dependable on the capacity level. This assumption will be discussed in Sect. 6 of this paper. The cost function can be written as follows:

$$C(v) = \sum_{t=1}^{n} C_t(v_t) + \sum_{i=1}^{n} CR_i \tag{5}$$

where $n$ is the number of capacity scalability points and $n$<$T$.

This cost function is assumed to be concave. This assumption is supported by Manne [4], who showed that the cost function of capacity addition for different studied industries is expressed as a power function or as a power function pieced together with a linear function (as in this case) and both are concave functions. Also, Luss [6] stated that most of the capacity expansion (scalability) functions are concave, representing the economies of scale of the expansion sizes. The exact calculation of the cost function (with its two terms) for capacity scalability in an RMS with all of the parameters involved is a research area that needs a lot of enhancements; however, these calculations are beyond the scope of this paper and will not affect the validity of the model.

### 4.3 Regeneration point (scalability point)

A point of regeneration of a capacity scalability schedule or plan $v$ is said to occur in period $t$ if $Z_t$ (the end of period excess capacity)=0. In an RMS, the capacity planning is a series of regeneration or scalability points. This fact enables us to use the regeneration point theorem that states that “there is an optimal capacity schedule which has the regeneration point property” [14].

The theorem is based on the previous facts that the capacity schedules set is a closed, bounded convex set, and that the cost function is a concave function and manipulates the previously stated property. The extreme points where the cost of capacity policy is minimum, based on the regeneration point theorem, are the scalability points or the points at which the system capacity planner will scale the capacity up or down. Such an optimum schedule will be found using a genetic algorithm (GA) approach.

## 5 Optimal capacity scalability scheduling tool formulation

Let one scalability point occur at period $i$ and the next scalability point occur at period $k$ (with $i$<$k$). Then, necessarily, there is an integer $i$+1≤$k$, such that:

$$v_{i+1} = \sum_{t=i+1}^{k} D_t \tag{6}$$

It should also be recalled that the points $t$=0 and $t$=$T$ are always regeneration points.

### 5.1 Applying a genetic algorithm technique to capacity scalability scheduling in an RMS

Genetic algorithms (GA) is a population-based model that uses selection and recombination operators to generate new sample points in the solution space. A GA encodes a potential solution to a specific problem on a chromosome-like data structure, and applies recombination operators to these structures in a manner that preserves critical information. Reproduction opportunities are applied in such a way that those chromosomes representing a better solution to the target problem are given more chances to reproduce than chromosomes with poorer solutions. GA is a promising heuristic approach to locating near-optimal solutions in large search spaces problems, such as the problem of scheduling. For a complete discussion of GAs, the reader is referred to Gen and Cheng [15].

Typically, a GA is composed of two main components, which are problem-dependent: the encoding problem and the evaluation function. The encoding problem involves generating an encoding scheme to represent the possible solutions to the optimization problem. In this paper, a candidate solution (i.e., a chromosome) is encoded to represent valid schedules for all of the demand over the capacity scalability planning horizon *T*. The evaluation function measures the quality of a particular solution. Each chromosome is associated with a fitness value, which, in this case, is the cost of the corresponding schedule represented by the given chromosome. For this research, the lowest fitness value represents the best solution obtained. The "fitness" of a candidate schedule is calculated here based on the physical cost ($C_t(v_t)$) of the capacity unit and the associated cost of reconfiguration ($CR_i$). Figure 1 outlines the capacity scalability schedules generation using GAs.

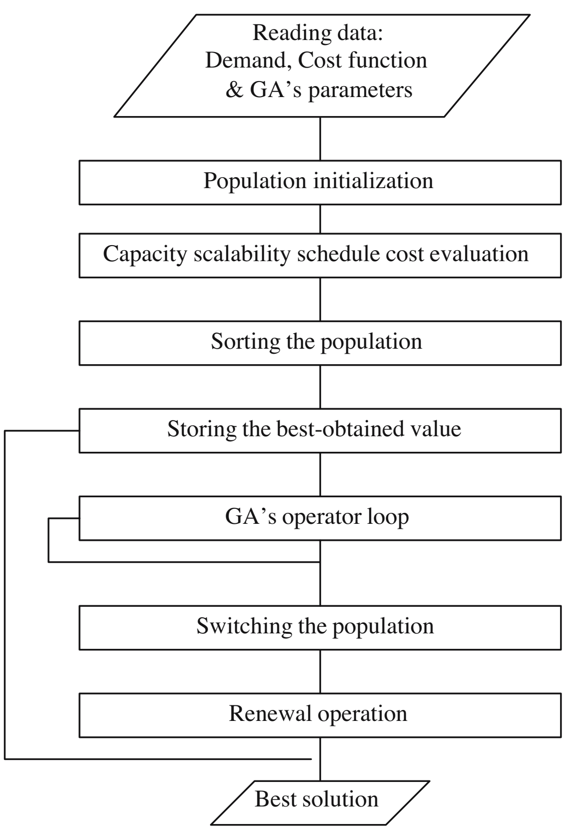


**Fig. 1** Capacity scalability schedules generation using GAs

5.2 Developing the capacity scalability scheduling tool

The previous analysis was used to develop a computer tool that takes the following inputs:

– Single period demand during the time $D_t$ ($t$=1, 2,..., $T$), where $T$ is the capacity planning horizon. It is assumed to be deterministic for simplicity.
– Capacity scalability cost function $C(v)$.

The output is the optimal capacity scalability schedule for the RMS. Figure 2 is an IDEF$_0$ representation of the proposed tool.

To validate the tool, the results generated by the tool was compared to the optimal results of the case study presented by Manne and Veinott [14]. The data were as follows: for a period $T$=6, $D_1$=0.5, $D_2$=1.0, $D_3$=1.5, $D_4$=1.5, $D_5$=1, and $D_6$=0.5, and the cost function is:

$$C(v) = 0.8^{(t-1)} \times (5 + (10 \times v_t)) \quad (7)$$

To be able to compare the results, the term representing the cost of reconfiguration (*CR*) in the cost function of the tool was omitted. The results generated by the tool are shown in Table 1. The results are exactly the same as the optimal results given by Manne and Veinott.

## 6 Investigating capacity scalability scheduling in RMS

In planning for the capacity of a manufacturing system, one can follow three approaches. The first approach is to construct a capacity at the beginning of the planning period ($t_1$) which is equal to all anticipated demand over the planning period (i.e., fixed capacity). This is the case in FMSs. The second approach is that, at each point over the planning period, one supplies a capacity that is equal to the demand at that point (i.e., capacity on demand), assuming that we have extreme reconfiguration ability. The third approach is to have an optimal capacity schedule that balances between the previous two approaches in satisfying the market demand at a minimum cost, which is the case in the proposed model (adaptive capacity).

The developed capacity scalability scheduling tool is used to illustrate the merit of this approach through calculating the cost associated with implementing each of

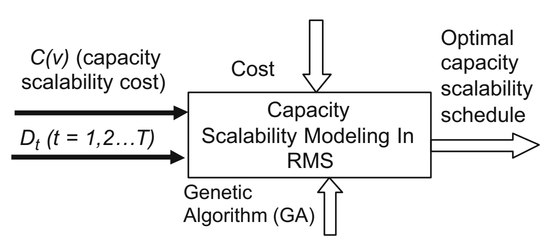


**Fig. 2** Developed capacity scalability scheduling tool

**Table 1** Capacity scalability scheduling tool results

| Scalability points ($t$) | Value of the scaled capacity | Cost |
|---|---|---|
| 1 (time unit) | 1.5 | 50.6 |
| 3 (time unit) | 3 | |
| 5 (time unit) | 1.5 | |

the three scheduling policies. This will be achieved through comparing the cost of each scheduling approach at different random fluctuating demand profiles. Table 2 shows the different generated deterministic demand values for one year.

As for the cost function, Eq. 7 will be adopted to represent the physical construction cost ($C_t(v_t)$) and the cost of reconfiguration ($CR$) will be represented by a linear function that multiplies the capacity scalability change between each scalability point by a constant that should vary according to the application (in this example, the constant equals 2). The difference between capacity scalability levels can reflect the degree of the system's physical reconfiguration carried out to meet the demand and, thus, it is used with a certain constant to express the term $CR$. For example, if the optimal capacity scalability schedule entitles that the capacity should be up-scaled by a small amount, an additional spindle to a machine can satisfy this need, while if the amount of scaling required is large, then an additional machine can be added. The cost of adding a spindle is much lower than adding a machine to the system. However, expressing the value of $CR$ could be represented by other forms, and should be indicated by the capacity planner based on the industrial application. The cost function will be as follows:

$$C(\mathrm{v}) = 0.8^{(\mathrm{t}-1)} \times (5 + (10 \times v_t)) + |\Delta C_t| \times 2 \qquad (8)$$

where $|\Delta C_t|$ is the capacity scalability change at scalability point $t$.

Figure 3 shows the cost of each capacity scheduling approach at each demand profile.

It is clear that the optimal capacity scalability schedules generated by the developed tool showed better performance in terms of cost in all demand scenarios over the other capacity scheduling policies. Also, as expected, the first policy that resembles the case of FMS is always the most costly policy, and this is one of the reasons for proposing the new RMSs.

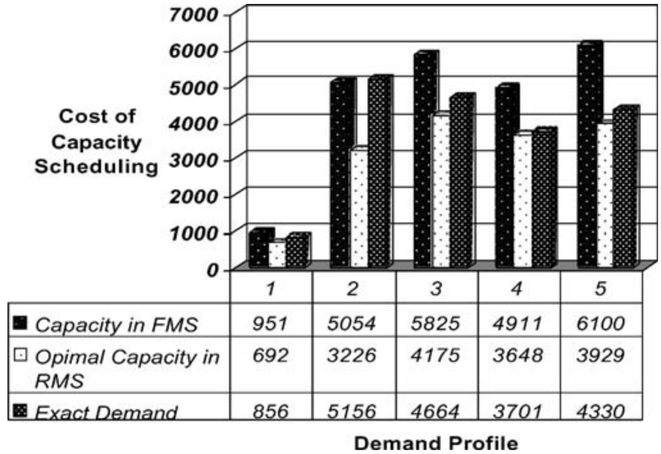


**Fig. 3** Cost of different capacity schedules at different demand profiles

Table 3 displays the output capacity scalability schedules generated using the scalability tool for the different demand profiles. One can recognize that the size of the capacity at each scalability point in these schedules is very close. This is because the cost of reconfiguration is expressed as a function of the difference between the capacity levels at each scalability point. Also, the number of scalability points is dependant on the constant used in the function of the cost of reconfiguration. This result shows that a cost-effective capacity scalability schedule in RMSs could be realized through decreasing the cost of the reconfiguration of these manufacturing systems.

## 7 Summary and conclusions

This paper presented a new approach to model the capacity scalability scheduling in reconfigurable manufacturing systems (RMSs). The model uses a cost function that includes both the cost of the physical capacity unit and the cost of reconfiguration associated with the system reconfiguration. Based on the model, a computer tool that manipulates the genetic algorithm (GA) technique for generating an optimal capacity scalability schedule was developed. The generated schedule indicates the points of capacity scalability over time and the required size to be scaled with at minimum cost.

The developed tool was used to explore three capacity scalability approaches with different demand profiles. The results showed the superiority of the optimal capacity scalability scheduling approach generated by the devel-

**Table 2** The generated deterministic demand values for one year

| $T$ (month) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $D_1$ | 10 | 5 | 3 | 12 | 8 | 9 | 4 | 6 | 11 | 5 | 3 | 10 |
| $D_2$ | 20 | 46 | 18 | 63 | 5 | 50 | 36 | 36 | 70 | 39 | 62 | 14 |
| $D_3$ | 50 | 41 | 66 | 19 | 33 | 77 | 26 | 15 | 38 | 49 | 60 | 55 |
| $D_4$ | 16 | 30 | 46 | 25 | 50 | 73 | 62 | 41 | 14 | 29 | 36 | 18 |
| $D_5$ | 37 | 44 | 22 | 58 | 39 | 66 | 71 | 53 | 47 | 18 | 29 | 70 |

**Table 3** Optimal capacity scalability schedules for different demand profiles

| Demand profile | Scalability point | Capacity level |
|---|---|---|
| $D_1$ | 1 | 38 |
| | 6 | 48 |
| $D_2$ | 1 | 238 |
| | 8 | 221 |
| $D_3$ | 1 | 286 |
| | 7 | 243 |
| $D_4$ | 1 | 246 |
| | 7 | 200 |
| $D_5$ | 1 | 266 |
| | 7 | 288 |

oped tool over both the instantaneous capacity change approach and the approach of supplying all required capacity at the beginning of the planning period in terms of cost in all of the demand profiles considered. The generated capacity scalability schedules highlighted the fact that the level of the capacity to be scaled and the cost of the capacity scalability schedule in RMSs are related to the cost of reconfiguration of the system. Thus, the cost-effective implementation of an RMS depends highly on decreasing the cost of reconfiguration of these systems.

An extension of this work can include considering stochastic demand patterns and investigating the logical capacity scalability alternatives. In addition, the modeling of the cost of reconfiguration in an RMS is a potential topic that has to be tackled in order to prove the cost-effectiveness of RMSs over other classical systems.

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