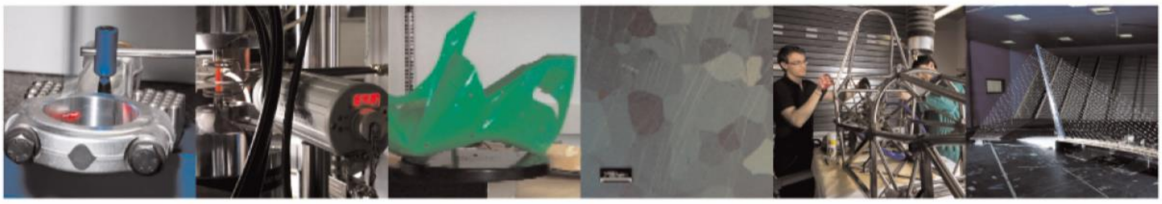

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Scalability in Manufacturing Systems: A Hybridized Genetic Algorithm Approach

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Scalability in Manufacturing Systems: A Hybridized GA Approach

As one of the key characteristics in manufacturing systems, scalability plays an increasingly important role that is driven by the rapid change of market demand. It provides the ability to rapidly reconfigure production capacity in a cost-effective manner under different situations. Our industrial partners face scalability problems involving multi-unit and multi-product manufacturing systems. In this paper, a hybridized genetic algorithm (GA) approach is presented to solve these kinds of problems. A mathematical model is defined by considering technological and capacity as well as industrial constraints. Starting from the original process plan and configuration of the manufacturing system, a set of practical principles are built to reduce the time associated with finding a feasible solution. An improved GA is proposed to search in the global solution space; the method is hybridized with a heuristic approach to locally improve the solution between generations. A balancing objective function is defined and used to rank the solutions. Experiments are set to determine the most adequate parameters of the algorithm. An industrial case study demonstrates the validity of the proposed approach.

Keywords: Manufacturing system; Reconfiguration; Scalability; Genetic algorithm; Industrial case study

1 Introduction

In this paper, we tackle the problem of manufacturing system reconfiguration starting from a real case study. The industrial case study refers to the production of engine blocks. This is done in a plant characterized by multiple manufacturing units that each produce a part in the same part family. Each unit has a number of stations that have identical machine tools with flexible fixtures, and the units are reconfigurable with respect to the part family. However, changeable demands and product upgrades urge the company to frequently adjust the manufacturing units. To deal with this problem, engineers usually change the station configuration inside the manufacturing unit, the number of machine tools per station, the fixture configurations, and the operation allocation to the stations. By applying non-dedicated reconfiguration approaches, this activity becomes too time consuming to reach a satisfied solution, which results in profit loss. Therefore, the industrial company seeks to determine the best way for how to reconfigure the single manufacturing unit and "re-balance" it to rapidly meet changeable demands.

This manufacturing system reconfigurability problem is well known as the "scalability" problem. In this contest, scalability may be defined as the ability to adjust the production capacity of a system through system reconfiguration with minimal cost in minimal time over a large capacity range at given capacity increments (Spicer et al. 2002).

A relevant review on this subject shows the scalability potential for resolving several problems in manufacturing systems (Putnik et al. 2013). It was first introduced in the late 1990s by Koren et al. (1998). Since then, some research works were presented to solve this problem. Son et al. (2001) presented one of the few approaches focusing on capacity scalability, which is combined with a line-balancing problem. Although this application was only limited to upgrading for serial lines through the replication of an existing station, the subject is still of great interest due to the great uncertainty in today's market, as discussed by Deif and ElMaraghy (2016)

Despite the vast literature on reconfigurable manufacturing systems, the scalability problem tackled in this paper remains largely unaddressed. The most relevant and similar research on the problem has been presented by Wang and Koren (2012, 2017). Initially, they introduced a method to design a multi-stage machining line using a genetic algorithm, and recently they presented a further improvement, in which the volume of each buffer was considered in the model. As the production demand changes, the number of stations is kept unchanged, and machine tools can be added or removed from the stations. Then, the production line with the new configuration is re-balanced. To this state, a general approach was presented to re-design the sequence of operations through constraints such as technological precedents among machining operations. Limitations of the paper are related to the possibility to reproduce the proposed GA as well as incomplete information related to the case study.

However, in our situation, due to machining precision and reconfiguration time, manufacturers prefer to keep some operations related to the important features fixed on the original plan, which means that the original fixture and certain machining operations should be kept in the original station of the manufacturing unit. Therefore, we address the situation in which the reconfiguration is limited and based on previous well known and accepted plans.

This paper introduces a new hybridized GA approach for this kind of scalability problem. A practical optimization method is presented to reconfigure an existing system driven by new market demands from the point of view of both the selection of the optimal manufacturing unit configuration and the definition of the best line balancing. Therefore, this paper is structured as follows: Section 2 presents the mathematical model to describe the problem, Section 3 describes in detail the proposed solution approach, and Section 4 presents the industrial case study to validate the proposed approach. Our conclusions are summarized in Section 5. We report a detailed description of both the proposed solution approach and the industrial case study in order to guarantee reproducibility of the method and possibility to use the case study as a common testbed for other possible approaches.

2. Mathematical model

While the industrial case study refers to a multi-unit manufacturing system that is characterized by four independent units, this paper will focus on the single-unit scalability problem, whose model is presented in the following.

2.1 Assumptions

The following assumptions are made based on the real manufacturing case study:

A. All machine tools in the manufacturing unit are identical;
B. The number of stations in the manufacturing unit must remain constant during the manufacturing unit reconfiguration;
C. For each station, both the fixture and part orientation cannot be changed to serve for a set of fixed operations, which keep the quality of the parts;
D. If a station has two or more machine tools (station with parallel machine tools), each machine tool performs the same set of operations.

2.2 Inputs:

The model requires the following four sets of information:

(1) Production information;
(2) Manufacturing information;
(3) Configuration information;
(4) Product demand.

2.2.1 Production information

The available time of the manufacturing unit (T_A [hours/year]) can be calculated as

$$T_A = T \times IA \quad (1)$$

where T [hours/year] is the yearly total working time of the manufacturing plant, and IA [%] is the inherent availability of the manufacturing unit.

2.2.2 Manufacturing information

There are only two kinds of operations that must be allocated to the unit stations:

I. Fixed operations are those operations that must be kept in the original station due to Assumption C. The number of those operations is OPN_f.

II. Changeable operations are those operations that can be allocated to at least two among the unit stations. The constraints are due to technological precedence requirements in the considered process plan. The number of those operations is OPN_c.

Therefore, the total number of operation OPN is equal to

$$OPN = OPN_c + OPN_f \quad (2)$$

For each operation x_i where $i = 1..OPN$, the machining time $t_m(x_i)$ is known. Therefore, the total machining time for the product T_m can be calculated as

$$T_m = \sum_{i=1}^{OPN} t_m(x_i) \quad (3)$$

2.2.3 Configuration information

The manufacturing unit is composed of S stations: S_j with $j = 1..S$.

M_j is the number of machine tools allocated to the station S_j. Therefore, the total number of identical machine tools considered in the configuration is $M = \sum_{j=1}^{S} M_j$.

Each station S_j is characterized by three sets of operations. In fact, each operation x_i where $i = 1..OPN$ in the process plan can be classified with respect to the station S_j as the following:

I. Fixed operation: this means that, due to Assumption C, the operation must be executed in that station. The set of all fixed operations for station S_j is F_j.

II. Changeable operation: this means that, due to the process plan constraints, the operation could be executed in the station. The set of all changeable operations for station S_j is X_j.

III. Non-Feasible operation: this means that, due to the process plan constraints, the operation cannot be executed in that station. The set of all fixed operations for station S_j is NF_j.

Therefore, considering the operation x_i where $i = 1..OPN$, it can be either $x_i \in F_j$ or $x_i \in X_j$ or $x_i \in NF_j$.

2.2.4 Product demand

The scalability problem originates from the variability in product demand. Therefore, the new product demand D_{new} is a fundamental input to the model. Even if the new product demand is usually estimated every three months, it is given as the number of parts per year. To fulfil the new product demand D_{new} [parts/y], the expected cycle time CT_{Exp} [s/part] can be calculated as follows:

$$CT_{Exp} = \frac{T_A \times 3600}{D_{new}} \tag{4}$$

2.3 Decision variables

The decision variables of the problem may be subdivided in two sets:

(1) Configuration Adjustment Array, $CA(j)$ with $j = 1..S$; this describes how the configuration changes from the original one through an adjustment of machine tools, where $CA(j)$ is the number of machine tools added to station S_j. Therefore, $M_j = M_j^{old} + CA(j)$, where M_j^{old} is the number of identical machine tools originally allocated to station S_j.

(2) Operation Allocation Matrix, $\mathrm{OA(i,j)}$ with $\mathrm{i = 1..OPN}$ and $\mathrm{j = 1..S}$; this shows the reallocation of all operations based on the new configuration. $\mathrm{OA(i,j)}$ is an allocation matrix with the operation-to-station index $\mathrm{x_{ij}}$, which determines whether operation $\mathrm{x_i}$ is allocated to station $\mathrm{S_j}$:

$$x_{ij} = \begin{cases} 1 & \text{if } x_i \text{ is allocated to } S_j \\ 0 & \text{if } x_i \text{ is not allocated to } S_j \end{cases} \tag{5}$$

Apparently, $\forall x_i \in F_j \rightarrow x_{ij} = 1$, $\forall x_i \in NF_j \rightarrow x_{ij} = 0$, and $\forall x_i \in X_j \rightarrow x_{ij} \in \{0; 1\}$.

2.4 Relations and Constraints

Given a solution characterized by a configuration adjustment array $CA(j)$ and, therefore, by a number M_j of machine tools allocated to the station S_j and by an operation allocation matrix $OA(i,j)$, the following relations hold, and constraints must be verified.

2.4.1 Total machining time allocated to a station

The total machining time allocated to a station is the overall sum of the machining time of the operations allocated to the station S_j in terms of fixed and changeable operations:

$$T_{mj} = \sum_{x_i \in F_j} t_m(x_i) + \sum_{x_i \in X_j} t_m(x_i) = \sum_{i=1}^{OPN} x_{ij} \cdot t_m(x_i) \qquad (6)$$

2.4.2 Station Cycle Time

The station cycle time is the total machining time allocated to the station S_j divided by the number M_j of machine tools allocated to the station S_j:

$$CT_j = \frac{T_{mj}}{M_j} \qquad (7)$$

2.4.3 Ideal Cycle Time

The ideal cycle time CT_{Ideal} is introduced as the reference value of the cycle time, which is the perfect balancing situation. It is computed as the ratio between the total machining time T_m and the total number of machines M:

$$CT_{Ideal} = \frac{T_m}{M} \qquad (8)$$

2.4.4 Configuration constraints

There are four configuration constraints related to the considered solution.

The first one is that enough machine tools should be provided to satisfy the new demand:

$$M \geq M_{min} = \left\lceil \frac{T_m}{CT_{Exp}} \right\rceil \qquad (9)$$

This also means that it is always guaranteed that

$$CT_{Ideal} \leq CT_{Exp} \qquad (10)$$

The second one is that in each station there must be enough machine tools to complete all the fixed operations in the expected cycle time:

$$M_j \geq M_j^{\min} = \left\lceil \frac{\sum_{x_i \in F_j} t_m(x_i)}{CT_{Exp}} \right\rceil \tag{11}$$

The third one is that all the machines should be allocated to the stations:

$$\sum_{j=1}^{S} M_j = M \tag{12}$$

The fourth constraint is that each operation must be allocated to only one station:

$$\sum_{j=1}^{S} x_{ij} = 1,\ \forall i = 1..OPN \tag{13}$$

2.4.5 Production constraints

There is one main production constraint related to the considered solution. In fact, for each station, all allocated operations (fixed and changeable) should be completed in the expect cycle time to ensure the production volume to meet the demand:

$$\mathrm{CT_j} \leq \mathrm{CT_{Exp}} \tag{14}$$

2.5 Objective Function

This scalability problem is a combination of configuration selection and balancing problems. Therefore, the objective function will consider the two sub-problems.

Firstly, the total number of identical machine tools M is used to evaluate a configuration, and the goal is to minimize this number.

Secondly, the balancing problem is tackled. Among all possible objective functions that are typical of a balancing problem, two have been considered: the bottleneck time and the allocation time deviation.

The bottleneck time BNT is the maximum among the station cycle times:

$$\mathrm{BNT} = \mathrm{CT_{max}} = \max(\mathrm{CT_j}) \tag{15}$$

The BNT is able to put in evidence the station with the maximum workload; it stands for the cycle time of the whole machining line, which has a direct relationship with production volume. However, it ignores the balancing information of other stations inside the machining line, and this lack of information may make it hard to evaluate the allocation of operations among stations. Therefore, the bottleneck time BNT is computed for each solution, but it is not considered as the objective function.

With respect to the allocation time deviation, since CT_{j} is the station cycle time and CT_{Ideal} is the ideal cycle time in the case of perfect balancing, the deviation for each station S_j may be computed as the difference between the two values:

$$\Delta \mathrm{CT_j} = \mathrm{CT_j} - \mathrm{CT_{Ideal}} \tag{16}$$

Then, all allocation time deviations need to be combined. Among all possible approaches, two are the most relevant. The first approach considers the sum of the absolute deviations, $\sum_{j=1}^{S} \left| CT_{\mathrm{j}} - CT_{\mathrm{Ideal}} \right|$, which means that all of the values have the same weight. The second approach considers the sum of the square of the deviations, $\sum_{j=1}^{S} \left(CT_{\mathrm{j}} - CT_{\mathrm{Ideal}} \right)^2$, which means to combine the minimization of the overall deviation in order to have similar deviations among the stations. Higher deviations correspond to more critical stations. This is the reason why in this paper this second approach has been considered.

Therefore, the objective functions of the two sub-problems considered in this paper are:

$$\mathrm{OF_{Configuration}} = \min(\mathrm{M}) \tag{17}$$

$$\mathrm{OF_{Balancing}} = \min\left(\sum_{\mathrm{j=1}}^{\mathrm{S}} \left(\mathrm{CT_j} - \mathrm{CT_{Ideal}}\right)^2\right) \tag{18}$$

3. Proposed Solution Approach

In this section, a new approach is presented to solve this particular scalability problem. Firstly, the complete logic of the approach is shown. Then, principles for the configuration selection and the hybridized genetic algorithm are discussed in detail. Lastly, experiments are used to tune the parameters of the algorithm.

3.1 Solution Approach

The proposed approach is described by the logic diagrams shown in Fig. 1 and Fig. 2. The approach consists of five steps (Fig. 1).

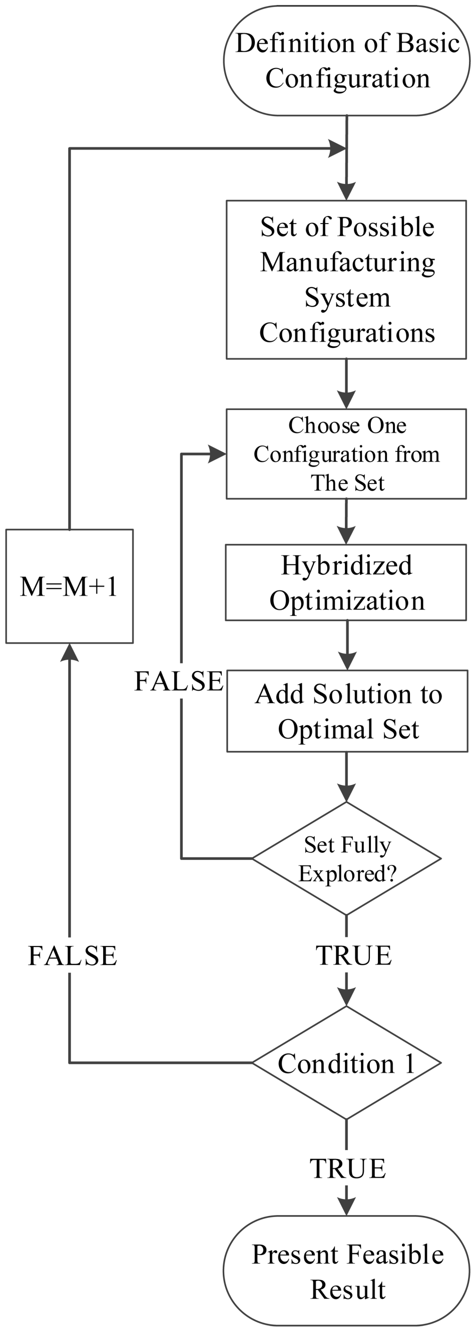

Fig. 1 Logic diagram of the proposed approach

Step 1: Define the initial configuration, which is organized as described in Section 2, and calculate M_{min} as the initial value of M.

Step 2: Generate the possible configuration set PS_{conf} with the current value of M, according to the principles described in Section 3.2.

Step 3: Fully explore all configurations in the possible configuration set PS_{conf} by hybridized optimization, and add the best solutions to the optimal set.

Step 4 Condition 1: Does the cycle time of the best solution in the optimal set meet the new production demand? If it is true, the feasible result is presented; otherwise, set $M = M + 1$ and return to Step 2. This means that the approach will add one machine tool at a time until the new product demand is satisfied (i.e., there is a feasible solution); so, the method will minimize the number of machine tools if the allocation operation algorithm or balancing algorithm is efficient.

St*ep 5:* Present solution group for ranked feasible results. Each result is given by the configuration adjustment array, $CA(j)$, and the operation allocation matrix, $OA(i,j)$.

Step 3 in the proposed approach relies on an allocation operation or balancing algorithm. The logic of this algorithm is shown in Fig.2, and it consists of nine sub-steps. In the following, a general overview of the algorithm is given, while further details will be discussed in Section 3.3.

Sub-Step 1: Create the initial population of possible allocations of all operations in the process plan by applying a mutation on the original solution (starting point of the scalability problem).

Sub-Step 2: Obtain an improved population of solutions through local optimization on each individual of the population.

Sub-Step 3: Calculate the fitness for the current population according to Eq. 18.

Sub-Step 4: Condition 2: Have all iteration times finished? If it is true, go to *Sub-Step 7*; otherwise, go to *Sub-Step 5*.

Sub-Step 5: With respect to the fitness calculation results, rank all individuals of the current population, and select the best individuals.

Sub-Step 6: Generate the next population by applying crossover and mutation operations as described in *Section 3.3*. Return to *Sub-Step 2*.

Sub-Step 7: Store the best individual of the population into an *Allocation Solution Set* as the result of the current run.

Sub-Step 8: Condition 3: Have all runs completed? If it is true, go to *Sub-Step 9*; otherwise, return to *Sub-Step 1*.

Sub-Step 9: Present the best solution from the *Allocation Solution Set* as the current chosen configuration.

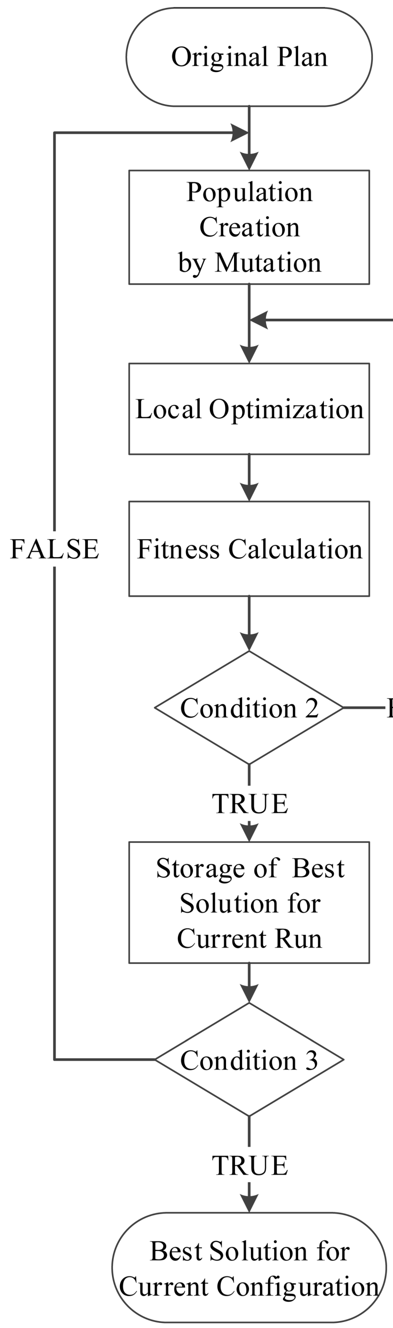

Fig. 2 Logic diagram of hybridized GA optimization

3.2 Principles for selecting possible configurations

3.2.1 Principle I

As the fixed operation set exists for each station, the number of machine tools of each station must guarantee the execution of at least the fixed operations. This minimum number can be computed as

$$\forall j = 1..S, \quad M_j^{min} = \left\lceil \frac{\sum_{x_i \in F_j} t_m(x_i)}{CT_{Ideal}} \right\rceil \tag{19}$$

where M_j^{min} is the minimum number of machine tools needed in station S_j. Note that the minimum number of machine tools for each station should not be less than 1, and usually if the demand increases it will not be less than the original number of machine tools.

3.2.2 Principle II

For each station, the *Changeable Operation Set* X_j shows all possible operations x_i that can be allocated to that station. The maximum machining time required to perform all operations in both the *Fixed Operation Set* F_j and the *Changeable Operation Set* X_j is used to limit the number of machine tools in the station S_j. Therefore, the maximum number of machine tools allocated to station S_j is M_j^{max}, and it can be calculated as

$$\forall j = 1..S, \quad M_j^{max} = \max\left[M_j^{min}, \min\left(M_j^{min} + \Delta M, \left\lfloor \frac{\sum_{x_i \in F_j} t_m(x_i) + \sum_{x_i \in X_j} t_m(x_i)}{CT_{Ideal}} \right\rfloor \right)\right] \tag{20}$$

where $\Delta M = M - \sum_{j=1}^{S} M_j^{min}$. The relevant portion of the equation is the min() function, while the max() is just to guarantee not to have a maximum number of machine tools lower than the minimum one. Note that the floor function in the min() function is relevant: the maximum number of machine tools M_j^{max} that can be allocated to station S_j is the largest integer less than or equal to the ratio between the maximum machining time that is required to perform all operations in both the fixed operation set F_j and the changeable operation set X_j and the ideal cycle time in the case of perfect balancing. This helps to avoid searching for a solution among configurations that are clearly non-efficient, which is the case when there is machine tool time that cannot be used by any operation in the process plan.

3.2.3 Principle III

Starting from the two values M_j^{min} and M_j^{max} for each station S_j, a station boundary matrix ST_b is built with ΔM rows and S columns as follows:

$$ST_b(i,j) = \begin{cases} 1 & \text{if i machine tools can be added to } S_j \\ 0 & \text{if i machine tools cannot be added to } S_j \end{cases} \tag{21}$$

According to ST_b and ΔM, PS_{conf} is finally built, which consists of all possible configurations with M machine tools.

3.3 Algorithm for operation allocation

3.3.1 Encode and decode

Based on the data of F_j, X_j, and NF_j set of operations for each station, a matrix $MI(i,j)$ is used to represent each individual of the population in the genetic algorithm. The length of each matrix is equal to the number of stations S, while the width of each matrix is equal to the number of changeable operations OPN_c. Each digit $MI(i,j)$ of the matrix contains information that links the station S_j to each operation $x_i \in X_j$. In particular, for each $i = 1..OPN_c$ and $j = 1..S$, the following holds:

$$\mathrm{MI(i,j)} = \begin{cases} 0 & \text{j is a not feasible station for operation i} \\ 1 & \text{j is a changeable station for operation i} \\ -1 & \text{j is the current station for operation i} \end{cases} \quad (22)$$

3.3.2 Initial Population

The original process plan with all the operations allocated to the stations is the starting point. From that point, a new population of solutions, whose dimension is N_{plan}, is initiated through mutation of the original solution.

3.3.3 Crossover and Mutation

In each generation, a number N_{top} of solutions that are highly ranked by the fitness calculation (using the objective function) are included in the next generation.

Crossover occurs between two different individuals in the current population. To reach the best solution and avoid a possible local convergence, two methods for selecting individuals are used:

- Crossover I occurs between one of the top individuals and another one chosen randomly;
- Crossover II selects both two individuals randomly.

During the crossover process, a single point is selected randomly to intersect the two $MI(i,j)$ at the same line and piece them together. In this way, the new individual generated by the crossover operation is kept feasible.

Mutation is applied randomly for each generation. Some individuals are randomly chosen in the current population. For each chosen individual, one changeable operation x_i [line *i* in $MI(i,j)$] is randomly selected, and then its current station S_j [column *j* where $MI(i,j) = -1$] is randomly exchanged with one station S_k among which the operation may be allocated [column k where $MI(i,k) = 1$].

3.3.4 Local Optimization

In order to reduce the convergence time of the algorithm, a heuristic approach is designed to improve the solution at each search step (each generation). In this situation, the most important part is to transfer the operations among stations to ensure a better balancing among the stations. So, the bottleneck station (S_{bn}), which has the maximum deviation time in the whole manufacturing unit, is chosen to be the pivotal station to do the "transfer work". In order to have more combinations and also follow the constraints, the station with the largest number of changeable operations in common with the bottleneck station S_{bn} is selected as the receiving station. Then, the objective function is calculated to evaluate all possible transfer of operations between the two stations. At last, the best solution is considered.

This overall approach is considered to be a "hybridized GA" due to this local optimization method based on an exhaustive local search.

3.4 Algorithm Parameters and Tuning Experiments

In order to run the proposed hybridized GA, we must set the values of many parameters. For each generation, the total plans (N_{plan}), which are the individuals of the current population, are the union of the top plans (N_{top}), the plans generated by mutation (N_m), and the plans generated by crossover (N_c). The crossover plans (N_c) may come from Crossover I (N_{ct}) or Crossover II (N_{cr}). Therefore, we must choose the number of each kind of plan and the total number of plans (individuals) in the current population. Moreover, we must choose the number of generations (N_{gen}) that must be considered in the evolution strategy of the GA to have an efficient sub-optimal solution as well as the number of iterations (N_{iter}) in the local optimization. Lastly, to guarantee a better sub-optimal solution, we also consider the possibility to run the full algorithm more than one time (N_{run}).

To carefully investigate these decisions, we perform a set of experiments. For each parameter, we explore different values (levels) and consider all of their possible combinations. The levels of the parameters considered in the experiments are reported in Table 1. Therefore, the number of considered experiments is $2^6 \times 3 = 192$. Three replicas for the same experiment have been considered. During the test, the sum of square of deviations has been considered as objective functions; nevertheless, the sum of the absolute deviation and the bottleneck are evaluated for each solution.

Table 1 Experiment setting for parameters tuning

Total Plan	Generation	Run	Iteration Times
N_{plan}	N_{gen}	N_{run}	N_{iter}
40 , 80	100, 500, 1000	10, 100	1, 10
Elitism Strategy	Mutation	Crossover I	Crossover II
N_{top}	N_m	N_{ct}	N_{cr}
10% , 20%	10% , 20%	40% / 60%	60% / 40%

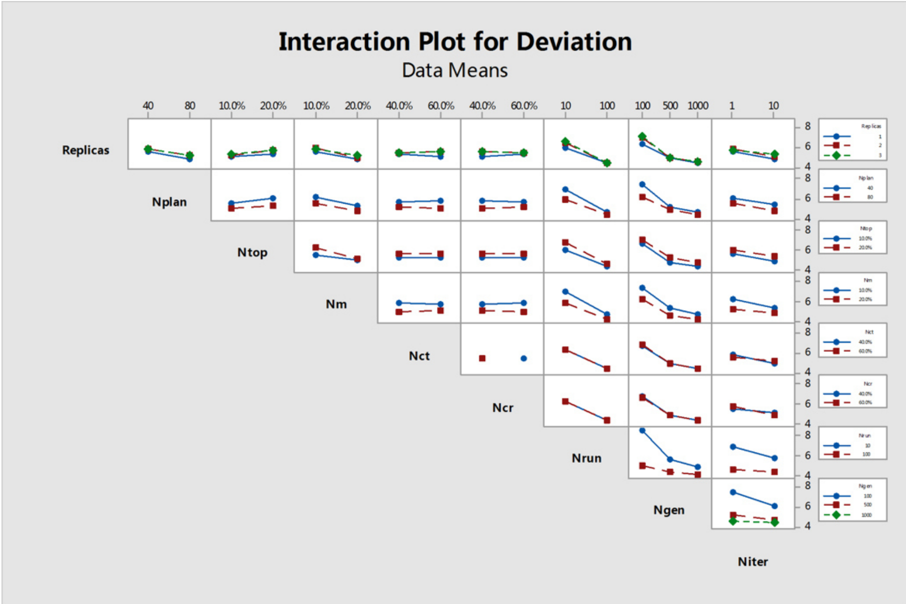

Fig. 3 Interaction plot for the sum of absolute deviations

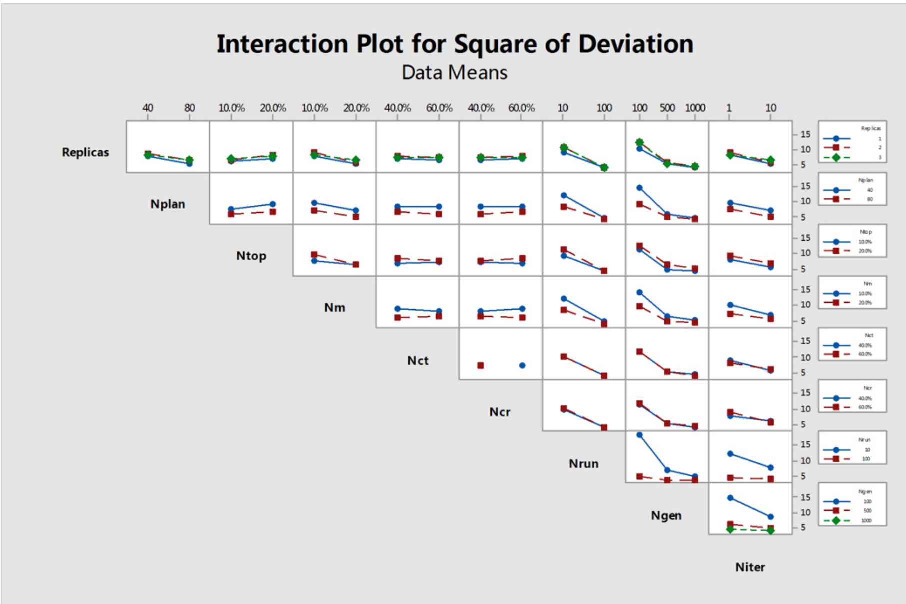

Fig. 4 Interaction plot for the sum of the squares of the deviations

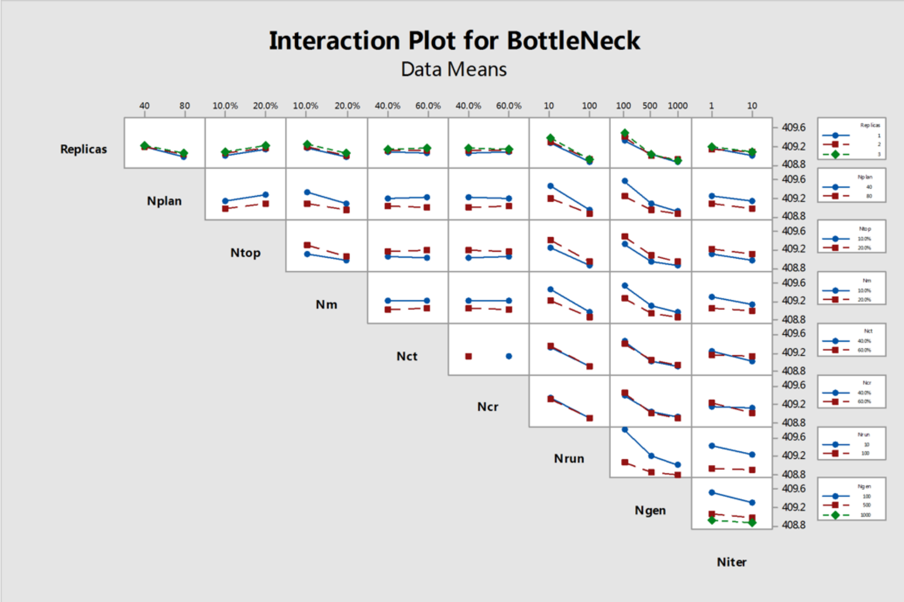

Fig. 5 Interaction plot for the bottleneck

As is shown in Figs. 3-5, the three different evaluations show similar behaviours. Decreasing N_{top} and increasing N_{plan}, N_m, and N_{iter} positively influence the method. However, different combinations of N_{ct} and N_{cr} seem to give similar results. N_{run} shows its great advantages to search for better solutions, while an increase of N_{gen} from 100 to 500 has a relevant effect on the solution, but relatively few improvement is made by increasing it to 1000. So, the parameter combination is chosen as shown in Table 2.

Table 2 Tuning results for parameters

Total Plan	Generation	Run	Iteration Times
N_{plan}=80	N_{gen}=500	N_{run}=100	N_{iter}=10
Elitism Strategy	Mutation	Crossover I	Crossover II
N_{top}=8	N_m=16	N_{ct}=22	N_{cr}=34

4. Case Study

This section presents a case study related to a cooperative project with an industry partner to validate our approach. In their manufacturing system, four kinds of cylinder blocks are produced by four different units in the same production plant. Recently, due to an increase of the market demand, the production of Part A (from Unit I) is planned to be increased from the original production of 25000 parts / year to the new production of around 35000 to 38000 parts / year.

The plant usually works on a two-shift per day base (8 hours per shift), 300 days per year with 90% inherent availability. As shown in Fig. 6, Part A is characterized by 211 features that require 504 machining operations, including drilling, deep drilling, boring, face milling, reaming, and tapping.

After the discussion on the basic plan with the company's process plan engineers, all 504 machining tasks are clustered into 72 different kinds of machining operations with 33 fixed operations and 39 changeable operations.

Unit I has 6 stations with a total of 9 identical machine tools, and its original configuration ($M_1^0 = 1$, $M_2^0 = 1$, $M_3^0 = 2$, $M_4^0 = 1$, $M_5^0 = 2$, $M_6^0 = 2$) is shown in Fig. 7. There are 4 kinds of different part positions for the 6 stations, which shows the accessibility of cutting tools for each station (Table 3). The original process plan is reported in Tables 4 and 5.

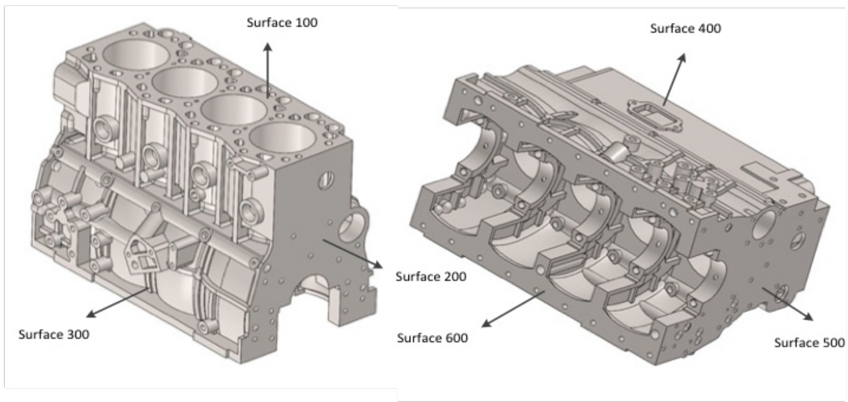

Fig. 6 3D model of the cylinder block - Part A

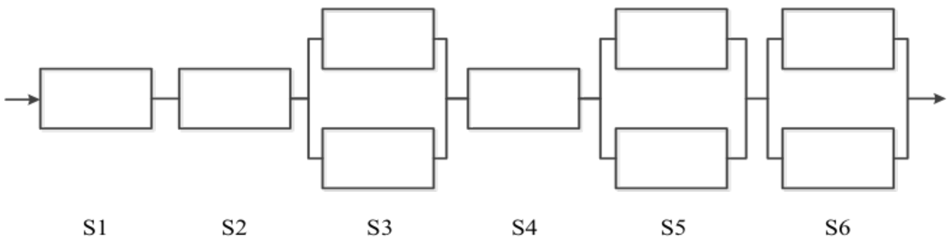

Fig. 7 Configuration of the original plan

Table 3 Original setups for 6 stations

Fixture	Part Orientation	Station	Reference Features
I	Surface 600 down	S1	Features from casting blank
II	Surface 300 down	S2, S5	300 Face with two holes (30101, 30104)
III	Surface 500 down	S3, S4	500 Face with two holes (50301, 50401)
IV	Surface 300 down	S6	600 Face with two holes (60101, 60102)

Table 4 Original process plan S1, S2, and S3

S1

Type	Not fixed operation	Operation Description	Machining Time [s]
F01	◆	32000 Face Milling	59.0
F02	◆	20000 Face Milling	49.0
F03	◆	50000 Face Milling	49.0
F04	◆	30101-30104 Boring and Reaming	52.6
F05	◆	50301/20901/21001 Boring and Reaming	38.4
F06	◆	50401/20401/20501 Drilling, Deep Drilling and Reaming	221.2
C01	1,2,5	20201/50201 Rough Boring	62.0
C02	1,2,5,6	21201/21401 Drilling	15.1
C03	1,2,5,6	21301 Drilling and Tapping	14.3
		STATION TIME	560.7

S2

Type	Not fixed operation	Operation Description	Machining Time [s]
F07	◆	60000 Semi-finish Milling	148.2
F08	◆	63000 Milling	112.2
C04	2,3,4,5	60101-60102 Drilling, Boring and Reaming	42.5
C05	2,4	60200 Rough Milling	189.1
C06	2,5	61601-61602/61501-61505/61401-61405 Face Milling	113.4
		STATION TIME	605.4

S3

Type	Not fixed operation	Operation Description	Machining Time [s]
F09	◆	10000 Semi-finish Milling	64.1
F10	◆	10101-10104 Rough Boring	330.2
F11	◆	40000 Finish Milling	38.3
F12	◆	30601 Drilling and Tapping	20.0
C07	3,5	10201-10202 Drilling and Boring	25.9
C08	3,5,6	10301-10316 Drilling, Boring and Tapping	204.8
C09	3,5,6	10401-10402 Drilling	9.4
C10	3,5,6	10601-10604 Drilling	18.4
C11	3,5,6	10701 Drilling and Deep Drilling	36.6
C12	3,5,6	10801 Drilling	8.0
C13	3,4	30201 Drilling and Tapping	15.8
C14	3,4	31301-31308 Drilling and Tapping	54.4
C15	1,3,4	30801 Drilling	7.5
C16	1,3,4	30901 Drilling	11.7
C17	1,3,4	31201 Drilling and Tapping	16.0
C18	1,3,4	31001-31002,31101-31102,31401-31402,31501-31502 Drilling and Tapping	86.8
C19	1,3,4	40401/40501-40508/40601 Drilling and Tapping	86.0
C20	1,3,4	40201-40204/40301 Drilling and Tapping	54.3
C21	1,3,4	40101-40102 Drilling and Tapping	21.5
		STATION TIME	1109.7

Table 5 Original process plan S4, S5, and S6

S5

Type	Not fixed operation	Operation Description	Machining Time [s]
F13	◆	60000 Finish Milling	73.5
F14	◆	61000 Finish Milling	75.6
F15	◆	61101-61108 Drilling, Boring and Reaming	235.8
F16	◆	20201\50201 Semi-finish Boring and Finish Boring	139.6
F17	◆	20301 Drilling and Boring	14.8
F18	◆	20701 Drilling and Boring	15.4
F19	◆	21701 Drilling, Boring and Tapping	22.1
F20	◆	20601 Drilling	7.9
F21	◆	20801 Drilling and Reaming	18.0
C25	1,2,5	21601 Drilling and Tapping	14.5
C26	1,2,5	21101-21117 Drilling and Tapping	94.6
C27	1,2,5	50801-50806,50901 Drilling and Tapping	53.9
C28	2,5,6	21501-21504 Drilling and Tapping	32.8
C29	2,5	50501-50502/50601-50602 Drilling and Boring	37.8
C30	2,5,6	50701-50708 Drilling and Tapping	52.8
C31	4,5	60201-60210 Drilling, Boring and Tapping	127.2
C32	2,4,5	60301-60318 Drilling and Tapping	103.3
C33	2,4,5	60401-60402,60501 Drilling and Tapping	36.1
C34	2,4,5	60601-60605 Drilling and Tapping	34.0
C35	2,4,5	60701/60801 Drilling	28.3
C36	2,4,5	60901-60904 Face Milling, Drilling and Tapping	40.5
C37	2,4,5	61001-61004 Drilling	15.6
		STATION TIME	1273.9

S4

Type	Not fixed operation	Operation Description	Machining Time [s]
F22	◆	61201-61205 Drilling and Deep Drilling	68.4
F23	◆	10501-10506 Face Milling, Drilling, Deep Drilling	143.1
C22	3,4	30401~30403/30301/30501 Face Milling, Drilling and Tapping	204.1
C23	3,4	30701 Drilling	18.4
C24	3,4	40701 Face Milling, Drilling and Tapping	58.6
		STATION TIME	492.5

S6

Type	Not fixed operation	Operation Description	Machining Time [s]
F24	◆	20000\50000 Finish Milling	173.7
F25	◆	20101\50101 Semi-finish/Finish Boring	373.3
F26	◆	20201\50201 Finish Boring	184.1
F27	◆	61601-61602 Finish Face Milling	99.3
F28	◆	20301 Reaming	9.5
F29	◆	20701 Reaming	9.7
F30	◆	21701 Reaming	9.0
F31	◆	10000 Finish Face Milling	71.2
F32	◆	10101-10104 Semi-finish/Finish Boring	232.0
C38	5,6	10201-10202 Reaming	15.0
C39	5,6	50601-50602,50501-50502 Reaming	24.8
		STATION TIME	1201.7

4.1 Market Demand $D_{new} = 35000\ parts/year$

Due to the demand and the available working time, the upper limit for the cycle time (CT_{Exp}) can be calculated as follows:

$$CT_{Exp} = \frac{T \times IA}{D_{new}} = \frac{300 \times 0.9 \times 16 \times 3600}{35000} = 444.34\ s$$

Then, $M_{\min}$ and its ideal cycle time CT_{Ideal} can be also obtained:

$$M_{\min} = \left\lceil \frac{T_m \times D_{new}}{T \times IA} \right\rceil = \left\lceil \frac{5243.87 \times 35000}{300 \times 0.9 \times 16 \times 3600} \right\rceil = \lceil 11.8 \rceil = 12$$

$$CT_{Ideal} = \frac{T_m}{M_{\min}} = \frac{5243.87}{12} = 436.99\ s$$

According to Principle I, the minimum number of machines for all of the stations $M_j^{\min}$ can be calculated as in Table 6; therefore, the minimum machine configuration to execute the fixed operations in each station will be $M_1^{\min} = 2$, $M_2^{\min} = 1$, $M_3^{\min} = 2$, $M_4^{\min} = 1$, $M_5^{\min} = 2$, $M_6^{\min} = 3$. This means a total of 11 machine tools are already allocated to the station, and at least 1 machine tool needs to be allocated to guarantee the new production demand.

Table 6 Minimum number of machine tools per station ($D_{new} = 35000$ parts/year)

	S1	S2	S3	S4	S5	S6
$\sum_{x_i \in F_j} t_m(x_i)$	469.25	260.36	452.52	211.43	602.57	1161.81
$\left\lceil \frac{\sum_{x_i \in F_j} t_m(x_i)}{CT_{Ideal}} \right\rceil$	$\lceil 1.07 \rceil$	$\lceil 0.60 \rceil$	$\lceil 1.04 \rceil$	$\lceil 0.48 \rceil$	$\lceil 1.38 \rceil$	$\lceil 2.66 \rceil$
$M_j^{\min}$	2	1	2	1	2	3

Apparently, there are 6 different ways to add a machine tool to the Unit I. In fact, a new machine tool could be added to only one of the 6 stations. However, when the maximum number of machines $M_j^{\max}$ is calculated according to Principle II, it gives 4 recommended choices in the 6 configurations (Table 7).

Based on the original configuration (machines in white), one machine is added to both station 1 and station 6 to satisfy the fixed operation time (M_{11} and M_{61} shown in Fig. 8). Then, four recommended choices (M_{22}, M_{32}, M_{42}, and M_{52} in black) are given to allocate the further machine tool according to Principle III. If one of these configurations is feasible, it corresponds to the minimum number of machine tools (optimal solution).

Table 7 Maximum number of machine tools per station ($D_{new} = 35000$ parts/y, time in [s])

	S1	S2	S3	S4	S5	S6
$\sum_{x_i \in F_j} t_m(x_i)$	469.25	260.36	452.52	211.43	602.57	1161.81
$\sum_{x_i \in X_j} t_m(x_i)$	538.09	980.65	980.78	1251.70	1261.81	432.20
$\sum_{x_i \in F_j \cup X_j} t_m(x_i)$	1007.34	1241.01	1433.30	1463.13	1864.38	1594.01
$\left\lfloor \frac{\sum_{x_i \in F_j} t_m(x_i) + \sum_{x_i \in X_j} t_m(x_i)}{CT_{Ideal}} \right\rfloor$	$\lfloor 2.31 \rfloor$	$\lfloor 2.84 \rfloor$	$\lfloor 3.28 \rfloor$	$\lfloor 3.35 \rfloor$	$\lfloor 4.27 \rfloor$	$\lfloor 3.65 \rfloor$
M_j^{max}	2	2	3	2	3	3

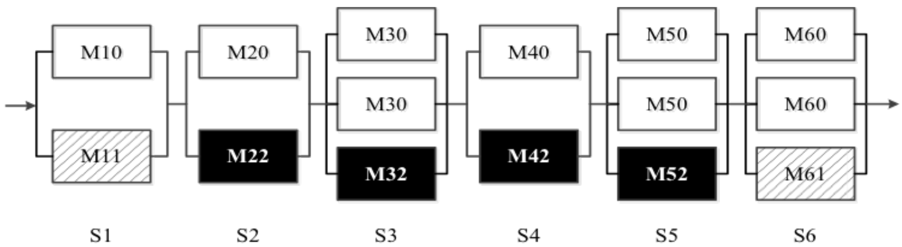

Fig. 8 Synthetic representation of possible configurations ($D_{new} = 35000$ parts/year)

Since the number of configurations is not very large, all 6 configurations are computed to check the performance of the principles. So, PG_{config} is shown in Table 8 with the recommended configurations in grey.

Table 8 Possible configuration set ($D_{new} = 35000$ parts/year)

PG_{config}	S1	S2	S3	S4	S5	S6
Configuration 1	3	1	2	1	2	3
Configuration 2	2	2	2	1	2	3
Configuration 3	2	1	3	1	2	3
Configuration 4	2	1	2	2	2	3
Configuration 5	2	1	2	1	3	3
Configuration 6	2	1	2	1	2	4

The hybridized algorithm with the tuned parameters has been applied to all configurations in the determined possible configuration set PG_{config}. The best results from each configuration are ranked in Table 9. It shows the following:

- Results associated with configuration 6 and configuration 1 are too far away from CT_{Exp} (i.e., they are unfeasible), thus proving the validity of Principle II;
- Considering the remaining four configurations, configuration 3 has the worst solution that is unfeasible with respect to the demand;
- Configurations 2 and 4 have the best performances, and they are also very similar; their sum of square deviations is in the range 0.2365 ± 0.0015 (0.6%).

Because of the close results between configurations 2 and 4, we expect the decision maker to use this information. The algorithm was run an additional 25 times for these two configurations to check the robustness of these results. The results are shown in Table 10. The best result is related to the configuration 4: $M_1^{\text{best}} = 2$, $M_2^{\text{best}} = 1$, $M_3^{\text{best}} = 2$, $M_4^{\text{best}} = 2$, $M_5^{\text{best}} = 2$, $M_6^{\text{best}} = 3$. The best allocation of the operations in this configuration 4 is shown in Tables 11 and 12 and enables an annual production of 35574 parts.

Table 9 Ranked optimal solution set for all possible configurations ($D_{new} = 35000$ parts/year, $CT_{Ideal} = 436.99$ s, $CT_{Exp} = 444.34\ s$)

Rank	Square [s^2]	Balance [s]	Bottleneck [s]	Production [parts/year]
Configuration 2	0.2354	1.0072	437.26	35567.0
Configuration 4	0.2383	0.7738	437.42	35554.2
Configuration 5	0.7029	1.6485	437.66	35534.7
Configuration 3	572.37	52.775	454.84	34192.5
Configuration 6	3178.3	127.69	459.12	33873.6
Configuration 1	15107	233.78	482.42	32237.3

Table 10 Further analysis of configuration 2 and configuration 4, according to Eq. 18

Test Number	Configuration 2 [s^2]	Configuration 4 [s^2]	Test Number	Configuration 2 [s^2]	Configuration 4 [s^2]
1	0.2274	0.1916	14	0.2274	0.1506
2	0.1966	0.1059	15	0.2263	0.2085
3	0.1723	0.1506	16	0.1966	0.1049
4	0.1966	0.1506	17	0.3704	0.1506
5	0.2274	0.1587	18	0.1966	0.2085
6	0.2274	0.1370	19	0.3704	0.2476
7	0.2263	0.1506	20	0.2274	0.1506
8	0.1966	0.1506	21	0.2274	0.2428
9	0.1146	0.2428	22	0.2274	0.1506
10	0.1966	0.1587	23	0.2274	0.0987
11	0.3417	0.0960	24	0.3138	0.1587
12	0.1723	0.2460	25	0.1966	0.1049
13	0.2274	0.1916			

Table 11 Optimal solution for configuration 4 ($D_{new} = 35000$ parts/year, S1, S2, S3, S4)

S1				S3			
Type	Not fixed operation	Operation Description	Machining Time [s]	Type	Not fixed operation	Operation Description	Machining Time [s]
F01	◆	32000 Face Milling	59.0	F09	◆	10000 Semi-finish Milling	64.1
F02	◆	20000 Face Milling	49.0	F10	◆	10101-10104 Rough Boring	330.2
F03	◆	50000 Face Milling	49.0	F11	◆	40000 Finish Milling	38.3
F04	◆	30101-30104 Boring and Reaming	52.6	F12	◆	30601 Drilling and Tapping	20.0
F05	◆	50301/20901/21001 Boring and Reaming	38.4	C08	3,5,6	10301-10316 Drilling, Boring and Tapping	204.8
F06	◆	50401/20401/20501 Drilling, Deep Drilling and Reaming	221.2	C09	3,5,6	10401-10402 Drilling	9.4
C01	1,2,5	20201/50201 Rough Boring	62.0	C10	3,5,6	10601-10604 Drilling	18.4
C18	1,3,4	31001-31002,31101-31102,31401-31402,31501-31502 Drilling and Tapping	86.8	C11	3,5,6	10701 Drilling and Deep Drilling	36.6
C19	1,3,4	40401/40501-40508/40601 Drilling and Tapping	86.0	C13	3,4	30201 Drilling and Tapping	15.8
C21	1,3,4	40101-40102 Drilling and Tapping	21.5	C14	3,4	31301-31308 Drilling and Tapping	54.4
C26	1,2,5	21101-21117 Drilling and Tapping	94.6	C15	1,3,4	30801 Drilling	7.5
C27	1,2,5	50801-50806,50901 Drilling and Tapping	53.9	C17	1,3,4	31201 Drilling and Tapping	16.0
				C24	3,4	40701 Face Milling, Drilling and Tapping	58.6
		STATION TIME	873.9			STATION TIME	874.1

S2				S4			
F07	◆	60000 Semi-finish Milling	148.2	F22	◆	61201-61205 Drilling and Deep Drilling	68.4
F08	◆	63000 Milling	112.2	F23	◆	10501-10506 Face Milling, Drilling and Deep Drilling	143.1
C29	2,5	50501-50502/50601-50602 Drilling and Boring	37.8	C04	2,3,4,5	60101-60102 Drilling, Boring and Reaming	42.5
C33	2,4,5	60401-60402,60501 Drilling and Tapping	36.1	C05	2,4	60200 Rough Milling	189.1
C34	2,4,5	60601-60605 Drilling and Tapping	34.0	C16	1,3,4	30901 Drilling	11.7
C35	2,4,5	60701/60801 Drilling	28.3	C20	1,3,4	40201-40204/40301 Drilling and Tapping	54.3
C36	2,4,5	60901-60904 Face Milling, Drilling and Tapping	40.5	C22	3,4	30401~30403/30301/30501 Face Milling, Drilling and Tapping	204.1
				C23	3,4	30701 Drilling	18.4
				C31	4,5	60201-60210 Drilling, Boring and Tapping	127.2
				C37	2,4,5	61001-61004 Drilling	15.6
		STATION TIME	437.1			STATION TIME	874.3

Table 12 Optimal solution for configuration 4 ($D_{new} = 35000$ parts/year, S5, S6)

S5				S6			
Type		Operation Description	Machining Time [s]	Type	Not fixed operation	Operation Description	Machining Time [s]
F13	◆	60000 Finish Milling	73.5	F24	◆	20000\50000 Finish Milling	173.7
F14	◆	61000 Finish Milling	75.6	F25	◆	20101\50101 Semi-finish/Finish Boring	373.3
F15	◆	61101-61108 Drilling, Boring and Reaming	235.8	F26	◆	20201\50201 Finish Boring	184.1
F16	◆	20201\50201 Semi-finish Boring and Finish Boring	139.6	F27	◆	61601-61602 Finish Face Milling	99.3
F17	◆	20301 Drilling and Boring	14.8	F28	◆	20301 Reaming	9.5
F18	◆	20701 Drilling and Boring	15.4	F29	◆	20701 Reaming	9.7
F19	◆	21701 Drilling, Boring and Tapping	22.1	F30	◆	21701 Reaming	9.0
F20	◆	20601 Drilling	7.9	F31	◆	10000 Finish Face Milling	71.2
F21	◆	20801 Drilling and Reaming	18.0	F32	◆	10101-10104 Semi-finish/Finish Boring	232.0
C03	1,2,5,6	21301 Drilling and Tapping	14.3	C02	1,2,5,6	21201/21401 Drilling	15.1
C06	2,5	61601-61602/61501-61505/61401-61405 Face Milling	113.4	C12	3,5,6	10801 Drilling	8.0
C07	3,5	10201-10202 Drilling and Boring	25.9	C28	2,5,6	21501-21504 Drilling and Tapping	32.8
C25	1,2,5	21601 Drilling and Tapping	14.5	C30	2,5,6	50701-50708 Drilling and Tapping	52.8
C32	2,4,5	60301-60318 Drilling and Tapping	103.3	C38	5,6	10201-10202 Reaming	15.0
				C39	5,6	50601-50602,50501-50502 Reaming	24.8
		STATION TIME	874.0			STATION TIME	1310.4

4.2 Market Demand $D_{new} = 38000$ parts/year

Considering the second situation in which the market demand is equal to 38000 parts per year, the optimization is performed following the same sequence of steps:

- The expected cycle time is calculated as

$$CT_{Exp} = \frac{T \times IA}{D_{new}} = \frac{300 \times 0.9 \times 16 \times 3600}{38000} = 409.93\ s$$

- The minimum number of total machines and ideal cycle time are calculated as

$$M_{\min} = \left\lceil \frac{T_m \times D_{new}}{T \times IA} \right\rceil = \left\lceil \frac{5243.87 \times 38000}{300 \times 0.9 \times 16 \times 3600} \right\rceil = \lceil 12.8 \rceil = 13$$

$$CT_{Ideal} = \frac{T_m}{M_{\min}} = \frac{5243.87}{13} = 403.37\ s$$

- According to Principle I, the minimum number of machine tools for each station is calculated as in Table 13.

Table 13 Minimum number of machine tools per station ($D_{new} = 38000$ parts/year, time in [s])

	S1	S2	S3	S4	S5	S6
$\sum_{x_i \in F_j} t_m(x_i)$	469.25	260.36	452.52	211.43	602.57	1161.81
$\left\lceil \frac{\sum_{x_i \in F_j} t_m(x_i)}{CT_{Ideal}} \right\rceil$	⌈1.16⌉	⌈0.65⌉	⌈1.12⌉	⌈0.52⌉	⌈1.49⌉	⌈2.88⌉
$M_j^{\min}$	2	1	2	1	2	3

- According to Principle II, the maximum number of machine tools for each station is calculated as in Table 14.

Table 14 Maximum number of machine tools per station ($D_{new} = 38000$ parts/y, time in [s])

	S1	S2	S3	S4	S5	S6
$\sum_{x_i \in F_j} t_m(x_i)$	469.25	260.36	452.52	211.43	602.57	1161.81
$\sum_{x_i \in X_j} t_m(x_i)$	538.09	980.65	980.78	1251.70	1261.81	432.20
$\sum_{x_i \in F_j \cup X_j} t_m(x_i)$	1007.34	1241.01	1433.30	1463.13	1864.38	1594.01
$M_j^{\min} + \Delta M$	4	3	4	3	4	5
$\left\lfloor \frac{\sum_{x_i \in F_j} t_m(x_i) + \sum_{x_i \in X_j} t_m(x_i)}{CT_{Ideal}} \right\rfloor$	⌊2.50⌋	⌊3.08⌋	⌊3.55⌋	⌊3.63⌋	⌊4.62⌋	⌊3.95⌋
$M_j^{\max}$	2	3	3	3	4	3

The possible configurations can then be defined (Fig. 9). Due to the fixed operation time, both station 1 and station 6 require one more machine (M_{11} and M_{61}), which is the same as the previously discussed situation. As two extra machines remain, there would be $C_6^2 + 6 = 21$ possible ways to allocate these machine tools to the stations. But, according to Principle III, the possible configuration set is created as shown in Fig. 9 (a black box represents where the machine tool could be added), and therefore, a set of 9 possible configurations has been defined (Table 15).

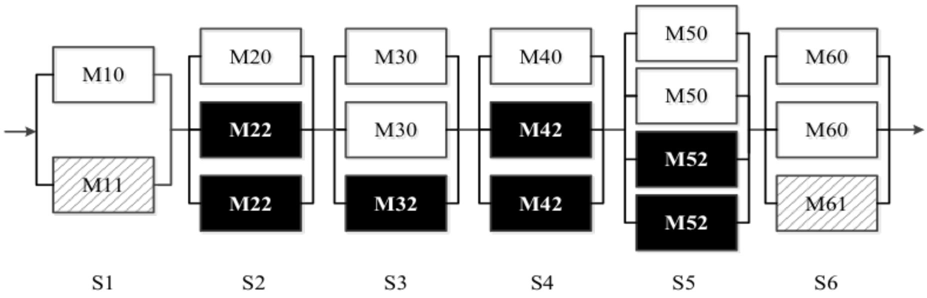

Fig. 9 Synthetic representation of possible configurations ($D_{new} = 38000$ parts/year)

Table 15 Possible configuration set ($D_{new} = 38000$ parts/year)

PG_{config}	S1	S2	S3	S4	S5	S6
Configuration 1	2	3	2	1	2	3
Configuration 2	2	1	2	3	2	3
Configuration 3	2	1	2	1	4	3
Configuration 4	2	2	3	1	2	3
Configuration 5	2	2	2	2	2	3
Configuration 6	2	2	2	1	3	3
Configuration 7	2	1	3	2	2	3
Configuration 8	2	1	3	1	3	3
Configuration 9	2	1	2	2	3	3

The hybridized GA with tuned parameters has been applied to all configurations in the determined possible configuration set PG_{config}. The best results from each configuration are ranked in Table 16. Because of the close results between configurations 5 and 6, again we have run the algorithm an additional 25 times for these two configurations. The results are shown in Table 17. The best result is related to the configuration 6: $M_1^{\text{best}} = 2$, $M_2^{\text{best}} = 2$, $M_3^{\text{best}} = 2$, $M_4^{\text{best}} = 2$, $M_5^{\text{best}} = 2$, $M_6^{\text{best}} = 3$. The best allocation of the operations for configuration 6 is shown in Tables 18 and 19: this configuration enables an annual production of 38546 parts.

Table 16 Ranked optimal solution set for all possible configurations (D_{new} = 38000 parts/year, CT_{Ideal} = 403.37 s, CT_{Exp} = 409.26 s)

Rank	Square [s^2]	Balance [s]	Bottleneck [s]	Production [parts/y]
Configuration 6	0.0248	0.3480	403.47	38545.6
Configuration 5	0.0332	0.3508	403.45	38547.3
Configuration 4	0.0490	0.4273	403.47	38545.3
Configuration 9	0.0721	0.5261	403.58	38534.7
Configuration 7	0.1164	0.5796	403.67	38526.8
Configuration 2	0.1192	0.6341	403.67	38526.8
Configuration 8	8.2182	3.9416	403.70	38523.4
Configuration.3	11.370	6.0990	404.25	38471.0
Configuration 1	95.509	21.770	408.81	38041.8

Table 17 Further analysis of configuration 6 and configuration 5, according to Eq. 18

Test Number	Configuration 6 [s^2]	Configuration 5 [s^2]	Test Number	Configuration 6 [s^2]	Configuration 5 [s^2]
1	0.0248	0.0362	14	0.0248	0.0369
2	0.0300	0.0332	15	0.0863	0.0332
3	0.0248	0.0332	16	0.0342	0.0369
4	0.0248	0.0366	17	0.0248	0.0369
5	0.0248	0.0338	18	0.0300	0.0338
6	0.0268	0.0317	19	0.0268	0.0362
7	0.0248	0.0362	20	0.0300	0.0332
8	0.0248	0.0338	21	0.0248	0.0362
9	0.0413	0.0332	22	0.0762	0.0326
10	0.0178	0.0332	23	0.0300	0.0332
11	0.0248	0.0332	24	0.0764	0.0362
12	0.0300	0.0317	25	0.0458	0.0335
13	0.0300	0.0338			

Table 18 Optimal solution for configuration 6 ($D_{new} = 38000$ parts/year, S1, S2, S3, S4)

S1

Type	Not fixed operation	Operation Description	Machining Time [s]
F01	◆	32000 Face Milling	59.0
F02	◆	20000 Face Milling	49.0
F03	◆	50000 Face Milling	49.0
F04	◆	30101-30104 Boring and Reaming	52.6
F05	◆	50301/20901/21001 Boring and Reaming	38.4
F06	◆	50401/20401/20501 Drilling, Deep Drilling and Reaming	221.2
C03	1,2,5,6	21301 Drilling and Tapping	14.3
C16	1,3,4	30901 Drilling	11.7
C17	1,3,4	31201 Drilling and Tapping	16.0
C18	1,3,4	31001-31002,31101-31102,31401-31402,31501-31502 Drilling and Tapping	86.8
C19	1,3,4	40401/40501-40508/40601 Drilling and Tapping	86.0
C20	1,3,4	40201-40204/40301 Drilling and Tapping	54.3
C25	1,2,5	21601 Drilling and Tapping	14.5
C27	1,2,5	50801-50806,50901 Drilling and Tapping	53.9
		STATION TIME	806.7

S2

Type	Not fixed operation	Operation Description	Machining Time [s]
F07	◆	60000 Semi-finish Milling	148.2
F08	◆	63000 Milling	112.2
C04	2,3,4,5	60101-60102 Drilling, Boring and Reaming	42.5
C05	2,4	60200 Rough Milling	189.1
C06	2,5	61601-61602/61501-61505/61401-61405 Face Milling	113.4
C29	2,5	50501-50502/50601-50602 Drilling and Boring	37.8
C30	2,5,6	50701-50708 Drilling and Tapping	52.8
C33	2,4,5	60401-60402,60501 Drilling and Tapping	36.1
C34	2,4,5	60601-60605 Drilling and Tapping	34.0
C36	2,4,5	60901-60904 Face Milling, Drilling and Tapping	40.5
		STATION TIME	806.7

S3

Type	Not fixed operation	Operation Description	Machining Time [s]
F09	◆	10000 Semi-finish Milling	64.1
F10	◆	10101-10104 Rough Boring	330.2
F11	◆	40000 Finish Milling	38.3
F12	◆	30601 Drilling and Tapping	20.0
C07	3,5	10201-10202 Drilling and Boring	25.9
C11	3,5,6	10701 Drilling and Deep Drilling	36.6
C15	1,3,4	30801 Drilling	7.5
C21	1,3,4	40101-40102 Drilling and Tapping	21.5
C22	3,4	30401~30403/30301/30501 Face Milling, Drilling and Tapping	204.1
C24	3,4	40701 Face Milling, Drilling and Tapping	58.6
		STATION TIME	806.7

S4

Type	Not fixed operation	Operation Description	Machining Time [s]
F22	◆	61201-61205 Drilling and Deep Drilling	68.4
F23	◆	10501-10506 Face Milling, Drilling and Deep Drilling	143.1
C13	3,4	30201 Drilling and Tapping	15.8
C14	3,4	31301-31308 Drilling and Tapping	54.4
C23	3,4	30701 Drilling	18.4
C32	2,4,5	60301-60318 Drilling and Tapping	103.3
		STATION TIME	403.3

Table 19 Optimal solution for configuration 6 ($D_{new} = 38000$ parts/year, S5, S6)

S5				S6			
Type		Operation Description	Machining Time [s]	Type	Not fixed operation	Operation Description	Machining Time [s]
F13	◆	60000 Finish Milling	73.5				
F14	◆	61000 Finish Milling	75.6	F24	◆	20000\50000 Finish Milling	173.7
F15	◆	61101-61108 Drilling, Boring and Reaming	235.8	F25	◆	20101\50101 Semi-finish/Finish Boring	373.3
F16	◆	20201\50201 Semi-finish Boring and Finish Boring	139.6	F26	◆	20201\50201 Finish Boring	184.1
F17	◆	20301 Drilling and Boring	14.8	F27	◆	61601-61602 Finish Face Milling	99.3
F18	◆	20701 Drilling and Boring	15.4	F28	◆	20301 Reaming	9.5
F19	◆	21701 Drilling, Boring and Tapping	22.1	F29	◆	20701 Reaming	9.7
F20	◆	20601 Drilling	7.9	F30	◆	21701 Reaming	9.0
F21	◆	20801 Drilling and Reaming	18.0	F31	◆	10000 Finish Face Milling	71.2
C01	1,2,5	20201/50201 Rough Boring	62.0	F32	◆	10101-10104 Semi-finish/Finish Boring	232.0
C08	3,5,6	10301-10316 Drilling, Boring and Tapping	204.8	C02	1,2,5,6	21201/21401 Drilling	15.1
C09	3,5,6	10401-10402 Drilling	9.4	C10	3,5,6	10601-10604 Drilling	18.4
C12	3,5,6	10801 Drilling	8.0	C38	5,6	10201-10202 Reaming	15.0
C26	1,2,5	21101-21117 Drilling and Tapping	94.6				
C28	2,5,6	21501-21504 Drilling and Tapping	32.8				
C31	4,5	60201-60210 Drilling, Boring and Tapping	127.2				
C35	2,4,5	60701/60801 Drilling	28.3				
C37	2,4,5	61001-61004 Drilling	15.6				
C39	5,6	50601-50602,50501-50502 Reaming	24.8				
		STATION TIME	1210.1			STATION TIME	1210.4

4.3 Market Demand $D_{new} = 15000\ parts/year$

In order to fully validate the proposed approach—even more generally than the current case study—a third situation in which the market demand decreases to 15000 parts per year is considered. The optimization is performed following the same sequence of steps:

- The expected cycle time is calculated as

$$CT_{Exp} = \frac{T \times IA}{D_{new}} = \frac{300 \times 0.9 \times 16 \times 3600}{15000} = 1036.8\ s$$

- The minimum number of total machines is calculated as from Eq. 9:

$$M \geq M_{\min} = \left\lceil \frac{T_m}{CT_{Exp}} \right\rceil = \left\lceil \frac{5243.87}{1036.8} \right\rceil = \lceil 5.06 \rceil = 6$$

- The minimum number of machines for all stations is calculated as from Eq. 11 and Eq. 12:

$$M = \sum_{j=1}^{S} M_j \geq \sum_{j=1}^{S} M_j^{\min} = \sum_{j=1}^{S} \left\lceil \frac{\sum_{x_i \in F_j} t_m(x_i)}{CT_{Exp}} \right\rceil = 7$$

- The ideal cycle time is calculated as

$$CT_{Ideal} = \frac{T_m}{M} = \frac{5243.87}{7} = 749.12\ s$$

- According to Principle I, the minimum number of machine tools for each station is calculated as in Table 20.
- According to Principle II, the maximum number of machine tools for each station is calculated as in Table 21.

Table 20 Minimum number of machine tools per station ($D_{new} = 15000$ parts/year, time in [s])

	S1	S2	S3	S4	S5	S6
$\sum_{x_i \in F_j} t_m(x_i)$	469.25	260.36	452.52	211.43	602.57	1161.81
$\left\lceil \frac{\sum_{x_i \in F_j} t_m(x_i)}{CT_{Ideal}} \right\rceil$	$\lceil 0.63 \rceil$	$\lceil 0.35 \rceil$	$\lceil 0.60 \rceil$	$\lceil 0.28 \rceil$	$\lceil 0.80 \rceil$	$\lceil 1.55 \rceil$
$M_j^{\min}$	1	1	1	1	1	2

Table 21 Maximum number of machine tools per station ($D_{new} = 15000$ parts/year, time in [s])

	S1	S2	S3	S4	S5	S6
$\sum_{x_i \in F_j} t_m(x_i)$	469.25	260.36	452.52	211.43	602.57	1161.81
$\sum_{x_i \in X_j} t_m(x_i)$	538.09	980.65	980.78	1251.70	1261.81	432.20
$\sum_{x_i \in F_j \cup X_j} t_m(x_i)$	1007.34	1241.01	1433.30	1463.13	1864.38	1594.01
$M_j^{\min} + \Delta M$	1	1	1	1	1	2
$\left\lfloor \frac{\sum_{x_i \in F_j} t_m(x_i) + \sum_{x_i \in X_j} t_m(x_i)}{CT_{Ideal}} \right\rfloor$	$\lfloor 1.34 \rfloor$	$\lfloor 1.66 \rfloor$	$\lfloor 1.91 \rfloor$	$\lfloor 1.95 \rfloor$	$\lfloor 2.49 \rfloor$	$\lfloor 2.13 \rfloor$
$M_j^{\max}$	1	1	1	1	1	2

Since $M_j^{\max} = M_j^{\min}$, when $M = 7$, there is only one possible configuration ($M_1^1 = 1$, $M_2^1 = 1$, $M_3^1 = 1$, $M_4^1 = 1$, $M_5^1 = 1$, $M_6^1 = 2$) (Fig. 10). Therefore, starting from the original configuration, two machines (M_{31} and M_{51}) can be freed from stations 3 and 5, and the possible configuration set has just one configuration.

Applying the hybridized GA for that single configuration, it is possible to find a balancing of 0.2719 s^2 according to Eq. 18 (0.8359 s, according to absolute balancing; 749.39 s, according to bottleneck balancing). The best allocation of the operations in this configuration is shown in Tables 22 and 23; this configuration enables an annual production of 20752 parts, and two machines are freed from Unit I.

Table 22 Optimal solution ($D_{new} = 15000$ parts/year, S1, S2, S3, S4)

		S1				**S4**	
Type	Not fixed operation	Operation Description	Machining Time	Type	Not fixed operation	Operation Name	Machining Time
F01	◆	32000 Face Milling	59.0	F22	◆	61201-61205 Drilling and Deep Drilling	68.4
F02	◆	20000 Face Milling	49.0	F23	◆	10501-10506 Face Milling, Drilling and Deep Drilling	143.1
F03	◆	50000 Face Milling	49.0	C13	3,4	30201 Drilling and Tapping	15.8
F04	◆	30101-30104 Boring and Reaming	52.6	C15	1,3,4	30801 Drilling	7.5
F05	◆	50301/20901/21001 Boring and Reaming	38.4	C16	1,3,4	30901 Drilling	11.7
F06	◆	50401/20401/20501 Drilling, Deep Drilling and Reaming	221.2	C21	1,3,4	40101-40102 Drilling and Tapping	21.5
C02	1,2,5,6	21201/21401 Drilling	15.1	C22	3,4	30401~30403/30301/30501 Face Milling, Drilling and Tapping	204.1
C03	1,2,5,6	21301 Drilling and Tapping	14.3	C23	3,4	30701 Drilling	18.4
C17	1,3,4	31201 Drilling and Tapping	16.0	C31	4,5	60201-60210 Drilling, Boring and Tapping	127.2
C19	1,3,4	40401/40501-40508/40601 Drilling and Tapping	86.0	C32	2,4,5	60301-60318 Drilling and Tapping	103.3
C26	1,2,5	21101-21117 Drilling and Tapping	94.6	C35	2,4,5	60701/60801 Drilling	28.3
C27	1,2,5	50801-50806,50901 Drilling and Tapping	53.9				
		STATION TIME	749.2			STATION TIME	749.1
		S2				**S3**	
F07	◆	60000 Semi-finish Milling	148.2	F09	◆	10000 Semi-finish Milling	64.1
F08	◆	63000 Milling	112.2	F10	◆	10101-10104 Rough Boring	330.2
C01	1,2,5	20201/50201 Rough Boring	62.0	F11	◆	40000 Finish Milling	38.3
C05	2,4	60200 Rough Milling	189.1	F12	◆	30601 Drilling and Tapping	20.0
C06	2,5	61601-61602/61501-61505/61401-61405 Face Milling	113.4	C04	2,3,4,5	60101-60102 Drilling, Boring and Reaming	42.5
C25	1,2,5	21601 Drilling and Tapping	14.5	C14	3,4	31301-31308 Drilling and Tapping	54.4
C28	2,5,6	21501-21504 Drilling and Tapping	32.8	C18	1,3,4	31001-31002,31101-31102,31401-31402,31501-31502 Drilling and Tapping	86.8
C33	2,4,5	60401-60402,60501 Drilling and Tapping	36.1	C20	1,3,4	40201-40204/40301 Drilling and Tapping	54.3
C36	2,4,5	60901-60904 Face Milling, Drilling and Tapping	40.5	C24	3,4	40701 Face Milling, Drilling and Tapping	58.6
		STATION TIME	748.7			STATION TIME	749.1

Table 23 Optimal solution (D_{new} = 15000 parts/year, S5, S6)

OP50				OP60			
Type	Not fixed operation	Operation Name	Machining Time	Type	Not fixed operation	Operation Name	Machining Time
F13	◆	60000 Finish Milling	73.5	F24	◆	20000\50000 Finish Milling	173.7
F14	◆	61000 Finish Milling	75.6	F25	◆	20101\50101 Semi-finish/Finish Boring	373.3
F15	◆	61101-61108 Drilling, Boring and Reaming	235.8	F26	◆	20201\50201 Finish Boring	184.1
F16	◆	20201\50201 Semi-finish Boring and Finish Boring	139.6	F27	◆	61601-61602 Finish Face Milling	99.3
F17	◆	20301 Drilling and Boring	14.8	F28	◆	20301 Reaming	9.5
F18	◆	20701 Drilling and Boring	15.4	F29	◆	20701 Reaming	9.7
F19	◆	21701 Drilling, Boring and Tapping	22.1	F30	◆	21701 Reaming	9.0
F20	◆	20601 Drilling	7.9	F31	◆	10000 Finish Face Milling	71.2
F21	◆	20801 Drilling and Reaming	18.0	F32	◆	10101-10104 Semi-finish/Finish Boring	232.0
C07	3,5	10201-10202 Drilling and Boring	25.9				
C10	3,5,6	10601-10604 Drilling	18.4	C08	3,5,6	10301-10316 Drilling, Boring and Tapping	204.8
C29	2,5	50501-50502/50601-50602 Drilling and Boring	37.8	C09	3,5,6	10401-10402 Drilling	9.4
C34	2,4,5	60601-60605 Drilling and Tapping	34.0	C11	3,5,6	10701 Drilling and Deep Drilling	36.6
C37	2,4,5	61001-61004 Drilling	15.6	C12	3,5,6	10801 Drilling	8.0
C38	5,6	10201-10202 Reaming	15.0	C30	2,5,6	50701-50708 Drilling and Tapping	52.8
				C39	5,6	50601-50602,50501-50502 Reaming	24.8
		STATION TIME	749.4			STATION TIME	1498.3

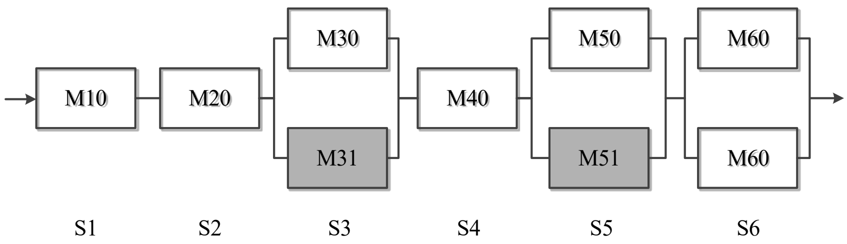

Fig. 10 Synthetic representation of possible configurations (D_{new} = 15000 parts/year)

5. Conclusion

This paper presented a hybridized approach to solve a particular scalability problem to meet the continuous change of market demand. Heuristic principles driven by operation constraints have been designed to find feasible configuration sets with a minimal number of machine tools, and we proposed a hybridized genetic algorithm to search for the optimal balanced solution. A complete industrial case study with two real new market demand requirements has been used to validate our approach. The experimental results showed that the scalability problem can be easily solved efficiently and effectively using the proposed approach. Future research can improve upon this approach by including multi-units (e.g., re-organizing units and sharing machines) within the scalability problem.

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