Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 62 (2017) 1 – 2

www.elsevier.com/locate/procedia

# 10th CIRP International Conference on Intelligent Computation in Manufacturing Engineering - CIRP ICME '16 Editorial

R. Teti[a,b,*]

[a]*Department of Chemical, Materials and Industrial Production Engineering, University of Naples Federico II, P.le Tecchio 80, 80125 Naples, Italy*
[b]*Fraunhofer Joint Laboratory of Excellence on Advanced Production Technology, Fh-J_LEAPT Naples, P.le Tecchio 80, 80125 Naples, Italy*
*Tel.: +39-081-7682371; Fax: +39-081-7682362; *E-mail address:* roberto.teti@unina.it

This Procedia CIRP volume contains the Proceedings of the *10th CIRP International Conference on Intelligent Computation in Manufacturing Engineering (CIRP ICME '16)*, 20 - 22 July 2016, Ischia, Italy, with focus on *Innovative and Cognitive Production Technology and Systems*.

The *CIRP ICME Conference Series*, founded by Prof. R. Teti in 1998 with the first edition strongly encouraged by Dr. Eugene Merchant and supported through his personal participation, resulted from the activities of the *Working Group on Applications of Artificial Intelligence Methods in Manufacturing Engineering*, chaired by Prof. R. Teti within the *Scientific-Technical Committee "O" (STC–O)* of the *International Academy for Production Engineering (CIRP)*.

The response to the *10th edition of the CIRP ICME Conference* in terms of number of submitted papers and their quality has confirmed the widespread interest in Intelligent Computation in Manufacturing Engineering, covering the whole of Production Engineering Research.

The 108 accepted papers and 4 keynote papers were presented by authors from 24 countries and 5 continents, witnessing an altogether worldwide spread interest. The topics dealt with ranged from Manufacturing Systems issues (System Modelling, Design, Planning and Control; Supply & Production Networks; Machine Tools; Flexibility, Sustainability, Reconfigurability, Complexity; Assembly Systems; Logistics Systems), to Product related matters (Product Life Cycle, Product Development and Product Service), to Manufacturing Technology aspects (Subtractive Manufacturing, Additive Manufacturing, Forming Technologies, Laser Manufacturing, Metrology and Quality) as well as emerging issues such as Energy and Resource Efficiency, Cognitive Systems, Digital Factory, Cyber Physical Systems, Cloud Based Manufacturing, and the Industry 4.0 framework.

Last but not least, two Symposia where organized within this Conference edition with reference to Composite Materials Parts Manufacturing (CMPM, as an issues of the CIRP Collaborative Working Group on CMPM, and the International Workshop on Emergent Synthesis (IWES) in honour of its founder Prof. Kanji Ueda, Past President of the CIRP.

Through this wide range of research topics, this CIRP ICME Conference aimed at providing an international forum for the exchange of up-to-date knowledge information, experiences and results as well as the review of


Peer-review under responsibility of the scientific committee of the 10th CIRP Conference on Intelligent Computation in Manufacturing Engineering
doi:10.1016/j.procir.2017.03.003

progress and the discussions on the state-of-the-art and future trends of in intelligent computing methods and artificial cognitive systems in the various sectors of advanced manufacturing technology and systems.

The Conference represented an exciting opportunity for scientists and experts to meet, interact and share ideas about this highly dynamic research field. Last but not least, the Conference offered the opportunity to visit (or re-visit) Ischia, the “green” island in the Gulf of Naples, world wide famous for its beauty and enchantment, while concentrating on manufacture science and engineering issues.

I should like to express my deep gratitude to all the people and organisations that contributed to the realization and success of the Conference: Prof. G. Levy, Prof. J. Jeswiet, Prof. J. Fleischer and Prof. N. Nishino for their highly appreciated Keynote Papers presentations in the Plenary Session; the International Program Committee Members for their help and support; the Session Chairmen for stimulating and managing the technical discussions; the Referees for their expert advice and assistance; all the Authors for their high-level contributions and presentations in the Technical Sessions. Finally, let me thank the Conference Technical Secretary, Dr. D.M. D'Addona, and the Organising Committee Members for the hard work they have undergone: Prof. F. Capece Minutolo, Dr. A. Caggiano, Dr. T. Segreto; the Dept. of Chemical, Materials and Industrial Production Engineering personnel and graduate students as well as assistant staff for their energy and team-work: M. Carandente, D. Matarazzo, A. Bottillo, V. Balsamo, R. Angelone, A. Teti, A. Burraccione, D. Corradini, the youngest Conference participants: S. Corradini and F.S. Teti; and, last but not least, my wife Nunzia for her support in the organization of the Conference Social Events.

Particular thanks are due to the *International Academy for Production Engineering (CIRP)*, the main scientific sponsor of the *CIRP ICME Conference Series*, and the scientific co-sponsors of the event: the *Fraunhofer Joint Laboratory of Excellence on Advanced Production Technology (Fh-J_LEAPT Naples)* that contributed with participants from Germany and from Italy; and, finally, the Conference main supporting bodies: the *University of Naples Federico II* and the *Italian Ministry of Instruction, University and Research (MIUR)* are gratefully acknowledged for their organizational and financial assistance to the event activities.

Naples, July 2016

Roberto Teti
Chairman and Editor

Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 62 (2017) 147 – 152

www.elsevier.com/locate/procedia

10th CIRP Conference on Intelligent Computation in Manufacturing Engineering - CIRP ICME '16

# Hybrid flow shop management: multi objective optimisation

Lorenzo Lassig, Fabio Mazzer, Marino Nicolich*, Carlo Poloni

*Department of Engineering and Architecture, University of Trieste, via A.Valerio 10, 34127 Trieste, Italy.*

* Corresponding author. Tel.: +39 040 558 3825; fax: +0-000-000-0000. *E-mail address:* nicolich@units.it

**Abstract**

The objectives of the optimisation management that considers both assembly and production Hybrid Flow-Shops lines are several: optimal numbers of machines, shifts, product priority and time-period scheduling. The approach uses a combination of DES software with an MDO (Multidisciplinary Design Optimization) software.. The DES model is optimized following the process: 1) A Multi-objective Genetic Algorithm cycle generates a set of optimal solutions; 2) A Clustering cycle groups the solutions into different sets; 3) The selection of the preferred solution via post-processing; 4) A mono-objective optimisation of each cluster; and 5) creation of weekly scheduling with optimal results. Finally, application and results are described and discussed.



Peer-review under responsibility of the scientific committee of the 10th CIRP Conference on Intelligent Computation in Manufacturing Engineering

*Keywords:* Optimisation; simulation; management; production; flow;

## 1. Introduction

Currently, management and investigation of manufacturing systems is a very important aspect for any industry. The inaccurate or defective definition of manufacturing system can affect the real capacity of a company to stay in the market. For this reason in the last 20 years, several techniques to support the decision making have been developed in order to evaluate the manufacturing production strategies and the system itself.

The main purpose of production management is generally the scheduling of operations to maximize/minimize one or more performances. The literature shows several methods to solve problems of this type such as enumerative, heuristic and meta-heuristics methods.

In the first two cases, i.e. enumerative and heuristics, scientific papers examine a wide scenarios' spectrum [1], [2], [3]. In recent years, researchers have started to unite the heuristic method with iterative methods to find the optimal solution. This method is called metaheuristic method. The basic idea is to insert a random component inside a heuristic method. The repetition of such processes gives a better result than a purely heuristic one. The Multi-Objective Flow shop Scheduling Problem (MOFSP) [4] has been studied by researches who considered two or more objectives, such as makespan, flowtime, earliness, tardiness and idle time. Many types of optimisation algorithm are used, for example: *Simulated Annealing-SA, Tabu Search-TS, Genetic Algorithms-GA, Ant Colony Optimisation-ACO, Neural Networks-NN, etc.* [3], [5], [6], [7], [8], [9]. The latter methods lend themselves to connect with production systems simulation software, the Discrete Event Simulation tools (DES) that can simulate a wide range of activities and situations that may occur within a production system [9], even if significant computational time is needed [10]. Present work considers both assembly and process Hybrid Flow-Shop lines as case study. There are many definitions of HFS [11]. In general, HFS is defined as a set of $n$ jobs to be processed in $m$ stages. In our definition of HFS, the following assumptions are made:

- The number of processing stages $m$ is at least 2,
- Each stage has $k \geq 1$ machines in parallel and in at least one of the stages has $k > 1$,
- All jobs are processed following the same production flow: stage 1, stage 2,. . . , stage $m$. A job might skip any number of stages, assumed it is processed in at least one of them.
- Some jobs can have loops in the production system

The HFS problem is considerably more complex and intractable than conventional flow shop; it belongs to an N-P hard case. Due to these difficulties a precise method has not been found that solves every case in a reasonable time. In [12] the authors define the minimization of *Earliness* and maximization of *Tardiness* as objectives in order to meet the due date. On the other hand, [11] considers various methods



Peer-review under responsibility of the scientific committee of the 10th CIRP Conference on Intelligent Computation in Manufacturing Engineering
doi:10.1016/j.procir.2016.06.007

and objectives that are used for HFS: not only max *Earliness* and min *Tardiness*, but also minimize *makespan*, flow time, inventory cost, etc. Even if 60% of the cases consider minimizing the *makespan*, other objectives may be more important depending on the situation. Considering also the constraints and assumptions of real life cases, it is difficult that real HFS problems exactly match a model studied in literature. In many cases, for the best results the objective is not simply a mono-objective but multi-objective. Production scheduling problems are multi-objective by nature, and in most of the cases, these objectives are in conflict amongst themselves. The authors [13] consider solving a HFS scheduling problem by minimizing the *makespan* and inventory cost through a multi-objective-hybrid-metaheuristic approach, which combine genetic algorithm and variable neighbourhood search. They declare that the approach is robust, fast and simply structured.

This work faces also the inverse problem related to the definition of the production plant layout together with the production scheduling needed to meet prescribed production capabilities.

A typical approach to the design of the production system is therefore divided into 2 phases:

- 1. setting the general features of the production system
- 2. verifying if the production system can achieve a particular level of performances

Repeat phase 1 and phase 2 until the production system achieves the established performance avoiding undesired behaviours in the production system such as bottlenecks. DES tools can be used in the second phase to better understand the behaviour of the production system.

The method discussed here focuses directly on the performances and defines automatically the general features of the production system so that the performances can be achieved; in this method DES tool turns from a validation tool to a design tool.

In this case, the purpose of the optimisation is to find out the optimal general features: the right set of input variables so that the output achieves our goals. Thus, implying the idea that the performances are our objective and using optimisation as a research tool, the basis of the here discussed method is fixed. Therefore, this way of designing a production system, in comparison with the first one, is faster and gives the user more information.

The systems discussed here are two Hybrid Flow Shop with different objectives and constraints. Both of them use the same approach (chapter 2) to achieve their objectives. One is an assembly and testing plant of large mechanical products, which is described with its results in chapter 3, whereas the second is a processing production plant, described with its results in chapter 4. Finally, a conclusion is made in chapter 5.

## 2. Computing

In general, the mathematical behaviours of a production system are strongly non-linear and governed by numerous variables, whereas the performances, typically, are two or more. These two facts provide us with guidelines to design the computing phase that is directly linked with the choice of optimisation algorithm and the optimisation cycles.

The approach is to connect an optimisation cycle to a model that simulates the production using a discrete event simulation (DES) with WITNESS 14. The concept of the approach used to solve the problem is inserting variable inputs into a model that simulates the process flow. This model gives an output, which is compared with the main objective. This information is sent to the Genetic Algorithm (Esteco MODE-FRONTIER). Then, through the genetic algorithm, the inputs are changed accordingly (trying to improve the output) and inserted back into the model. The model will give another output and the loop is repeated. The number of iterations (loops) is defined at the beginning by the user. It is important to define the right number of iterations to have a sufficient number (although not too many) of optimal solution sets (fig.1.) The task of the genetic algorithm is changing inputs producing output from DES simulator that will converge to the objectives, not giving a single solution but a set of optimal solutions [14].

To increase the robustness of the genetic algorithm, it needs information on how the system works, for example, most critical variables and regions of optimal solution. The optimization algorithm is initialized by a set of configurations obtained by a DOE (Design of Experiment) technique.

A non-linear model can be well managed by a stochastic algorithm while gradient based methods cannot be used both because of the multi-objective natter of the problem as well as because the DES output cannot be derived. After the first cycle of multi-objective optimisation, with the help of the Pareto Front a set of optimal solutions are given. Each of these solutions are characterized by the fact that one objective cannot improve without worsening other objectives [15]. Since the optimal solutions can be very different among themselves as well as numerous, it is advisable to apply a clustering method to better understand the different features of the optimal solutions. Pareto Front is rearranged in clusters through a clustering method. For each cluster a second round of optimisation that maximizes the main objective is done. In the second round of optimisation, a mono-objective Simplex algorithm (greater accuracy), that needs a narrow set of optimal solutions (because less robust), is used to obtain a small set of optimal solutions (fig. 2) [16].

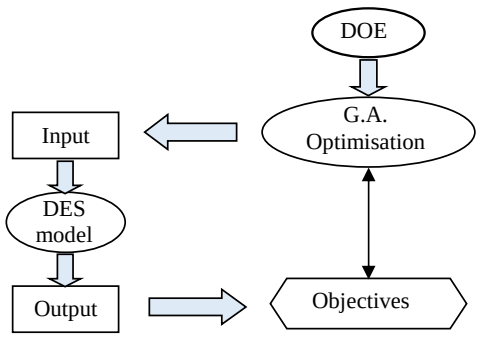


Fig. 1. Optimisation cycle

In the production test case (chapter 4), the same method of optimisation was used, but, in addition two decision support methods are used: Self-Organizing Map (SOM) [17] to project the high-dimensional data onto a two-dimensional map used to identify interest clusters and MCDM (Multi Criteria Decision Making) to choose the best solution considering the attributes and their preferences [13].

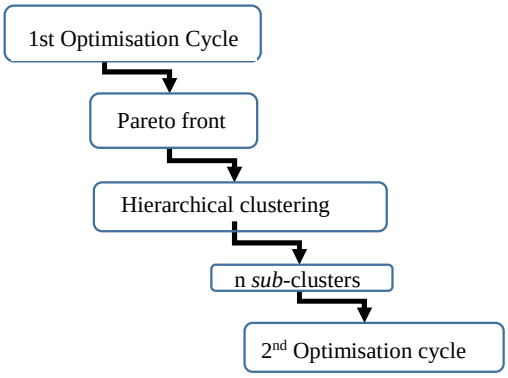


Fig. 2. Optimisation steps.

## 3. Assembly line test case

The line can handle the assembly of twelve different product typologies; the final products differ in size and in customization. Each product has its own Bill Of Materials (BOM); the twelve final products have been arranged into two subgroups depending on the size (*M*-Medium, *H*-High) and both subgroups count six products each. The main component identifies the main material flow line, while secondary component parts reach the corresponding station for assembling the main product component. The main component, Principal Part (PP), identifies the key element of the production process, but, due differing BOMs, there is the need for product customization and therefore sufficient flexibility in the assembly line to limit the setup times [18],[19]. For each machine-group station, the maximum number of available machines is known. Transportations between the stations uses a bridge crane that means the handling time is not negligible [20].
The management of secondary component parts (PS) finds place in two preparation departments, PS1 and PS2 (Fig. 3.).
The production capacity of these departments are considered much higher than that of the main assembly line in order to ensure that the process of the PP never waits for the arrival of secondary parts. The production mix and the production plan are given and it is assumed that during the simulation period of one year, the supply of PP and the corresponding PS is weekly: in total, every week five jobs enter, three of which are *M* type (3-*M*) and two are of *H* type (2-*H*).

### *3.1. First optimisation cycle*

The algorithm needs to be initiated by the use of DOE (Designs Of Experiment).
The goal of the DOE is to probe the dominion of solutions in such a way as to initialize the optimisation algorithm. From a practical point of view, it is defining: a) inputs and their variation rules, b) objective functions, c) constraints. The objectives are: minimum *Earliness* and *Tardiness* whereas the saturation level (ratio between the sum of the actual working time and the sum of time availability of the machine) of each machine-group is both optimised (around 80%) and constrained. Moreover no job can exceed the deadline.
At this stage, the genetic algorithm GA in MODE-FRONTIER uses the variables [21]: input priority of each PP, number of available machines and shifts for each machine-group. The input priority is the variable that regulates the "pull" rule at the beginning of the assembly line and it is associated with the final product (1=lowest priority;12=highest priority). Run has stopped at 14417-*th* design and the GA gives 55% of feasible designs, for which the constraints are respected, and 45% of designs when at least one constraint is violated; *constraint_busy* 88% and *deadline* 12% respectively.

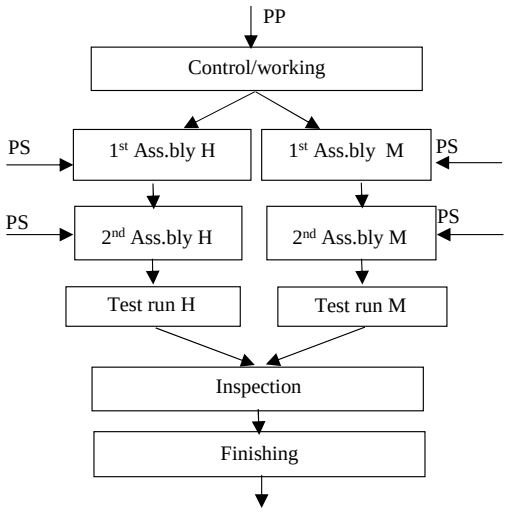


Fig. 3. Flow assembly line diagram

All results are plotted in Fig. 4. with *Tardiness* and *Earliness* v/s global *saturation level* (*SL*). Values in the diagrams, for easy reading, have been reduced to mean quantities with the global production volume:

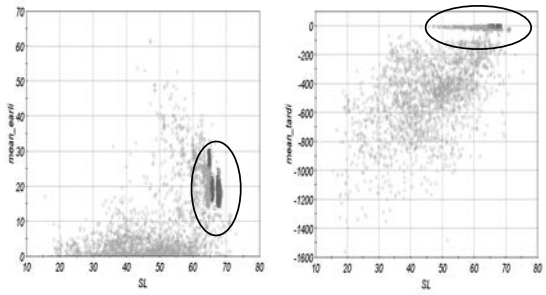


Fig. 4 : *Earliness* and *Tardiness* v/s utilisation percentage.

### *3.2. Second optimisation cycle and results*

Fig.5 shows the mean values of *Earliness/Tardiness* v/s *saturation levels* of the sub-clusters with confidence ellipse. A cycle of mono-objective optimization, the *Earliness* and *Tardiness* functions, will deal with the objective used on saturation levels of machine groups. The following polynomial is defined:

$$Early\_Tardi=(Earliness-K)^2+(Tardiness-K)^2 \qquad (1)$$

where $K$ is set to zero. Minimizing the polynomial tends to reduce the advance/delay of delivery. The number of stations and shifts for each machine-group stated in optimal conditions from *GA* optimisation and the input priority is the only variable:

***n***=[1,1,2,3,2,1,1,2,1], ***shift***=[3,3,2,3,3,2,3,2,2]

The designs belonging to cluster 1 are only different in terms of shifts and number of machines in comparison to other clusters. Since it has the lowest SL, cluster 1 will not be considered in the second optimisation cycle.
Tab.1 shows the three optimal precedence solutions, whereas Tab.2 shows the final results of the procedure and highlights that *Earliness* and *Tardiness* have opposite values in comparison of the starting solution (Sol). This behaviour is due to the fact that constraints for machines saturation levels appears very strong. On the other side, the saturation levels increase by about 10% .

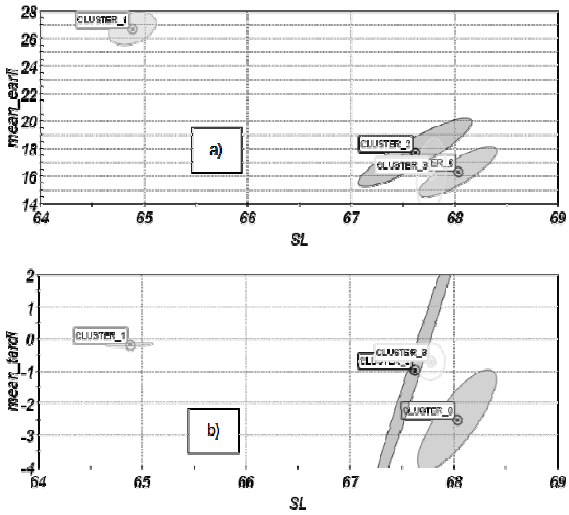


Fig. 5. Cluster groups.

Table 1. Second optimisation cycle results

| *Prio.* | *Clust. 0* | *Clust. 2* | *Clust.3* | *Prio.* | *Clust.0* | *Clust. 2* | *Clust. 3* |
|---|---|---|---|---|---|---|---|
| ***M1*** | 12 | 12 | 12 | ***H1*** | 10 | 11 | 10 |
| ***M2*** | 1 | 9 | 10 | ***H2*** | 6 | 2 | 1 |
| ***M3*** | 12 | 10 | 11 | ***H3*** | 4 | 3 | 1 |
| ***M4*** | 8 | 7 | 5 | ***H4*** | 2 | 4 | 2 |
| ***M5*** | 9 | 9 | 8 | ***H5*** | 1 | 2 | 1 |
| ***M6*** | 3 | 7 | 4 | ***H6*** | 5 | 6 | 6 |

## 4. Process flow test case

The system produces many types of products (more than 20) in various dimensions and the customer can impose some parameters as fixed requirements. Numerous product typologies add complexity to the system and for this reason only the most important flow routes shall be studied.

Table 2. Assembly line results

| | *clust. 0* | *clust. 2* | *clust. 3* | *1st Sol* |
|---|---|---|---|---|
| **Saturat. Level %** | 68 | 67 | 68 | 58 |
| **Earliness n°** | 3508 | 3357 | 3275 | 210 |
| **Mean Earl n°** | 15 | 15 | 14 | 1 |
| **Tardiness n°** | -662 | -227 | -225 | -4795 |
| **Mean Tard n°** | -3 | -1 | -1 | -21 |
| **Prod.Vol.M n°** | 138 | 138 | 138 | 137 |
| **Prod.Vol.H n°** | 90 | 90 | 90 | 88 |

In fact, most of the products shall be regrouped into part families with a standardized process. A brief introduction to the process-flow is shown in fig.6. Each product is represented by a letter A, B, C, D with a total of 4 final products. The letters E, F and H are a subgroup of the products and each block in the figure represents a machine group. Differently from the previous case the input priority is the variable that dictates the precedence of one product respect to another in the production system (1=lowest priority; 4=highest priority). The most critical machine groups are the selection and drying/washing since they are the bottlenecks of the system. One can notice that each route has a different production flow and some have loops, which create complexity in the system. Due to the great sales variation, the company programs the production plan twice a week.
The main difficulty is to control the complexity of the products and their process flow. Considering this, the best objective is to minimize the *makespan* (dominant objective), because it reduces the products process flow time. The percentage of saturation of a machine group is defined as the ratio of idle time and on-shift time. Therefore, the percentage of saturation measurement indicates the saturation of the machine group.

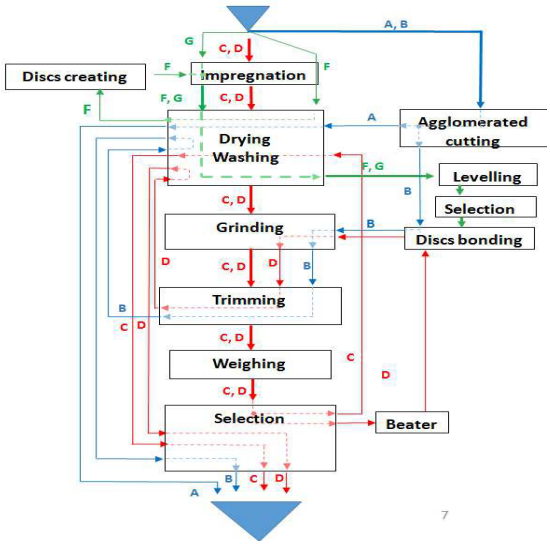


Fig. 6. Flow processing line diagram.

From the TOC [22], if the number of machines, shifts and operators increases at the bottleneck and the production line is kept balanced, the throughput increases and the time to market decreases.

The *Index Flow* (*IF*), *IF=ProcessTime/Lead Time*, replaces here the *makespan*.
*IF* is used because it gives information of how great the difference is between process time and lead time. Since the goal is to minimize the *makespan*, the *IF* should tend to 1 as much as possible. In this case the number of products in each buffer must not exceed a limit, due to insufficient space. To control the balance or imbalance of the workload in the various machine-groups, the minimum percentage of the machine groups saturation has introduced.
The priorities of the products are also considered as variable, since it gives more control on the flow and scheduling.
Using an objective function such as limiting the production unbalance, maximizing the throughput, limiting the buffer capacities and maximizing the *IF*, the following results have reached:
•Limiting percentage of minimum Saturation, of each machine group.
• Maximizing the total Throughput rate of the system.
• Limiting the capacity of each buffer.
• Maximizing *IF* of the products.
The same objectives has taken into account when using the MCDM and SOM post-processing tools.
The number of machines and operators per machine-group are considered. The model has the ability to vary this number between a minimum value and a maximum value. The same principle also applies to the number of shifts per day for each group-machine.
Managing the number of shifts, machines and operators allows the user to control unwanted behaviours of the production line, like bottlenecks and working load unbalances among the different machine groups.
The optimisation of a simulated 4 months forecast is done using the same approach as shown in fig. 2, with the addition of MCDM and SOM methods. The results will be compared amongst these methods and the preferred solution will be chosen. With the number of machines, priority of the products and the process flows determined, the new layout will be created. To demonstrate the complete control of the process flow, the optimal number of shifts for each weekly production launch will be found, thus showing the potential of dynamic scheduling. The most critical week of the 4 months period will be considered. To save time the number of machines, operators and priority of products are constant. On the other side, the daily shift for each machine group is the only variable. The number of available machines, operators and priority of each product are defined from the optimisation solution of the 4 months period. The objectives are identical to previous run.
To find the optimal weekly scheduling the MCDM is the fastest tool.

### *4.1. Results*

Similar to the assembly system, GA starts after the DOE has end. The GA uses the same input variables as the first case: priority, number of active machines and shifts for each machine-group. The run stopped with the 12507th design; GA gives 68% feasible designs and 32% unfeasible designs.
Fig 7, shows the total mean saturation and *IF* Saturation levels of the sub-clusters with confidence ellipse. One can notice that the clusters are very close, implying that each cluster with the mono-objective optimisation will give similar results.
Fig 8 (a). shows how different components are distributed on the SOM hexagonal grid. Similar component maps are placed in adjacent positions in order to spot correlations. Fig. 8 b) shows a SOM of *IF* component.
The variation between maximum and minimum of each component value is shown by colour variation. The highest values are in red (upper left corner) and the lowest in blue (the darkest spots).

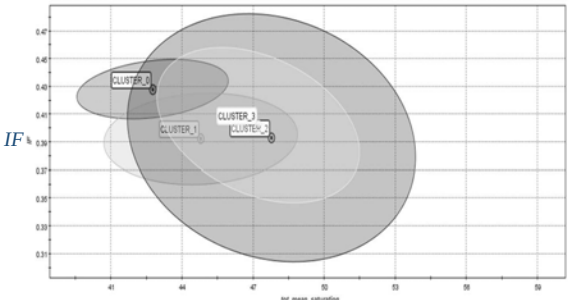


Fig. 7. Clusters groups

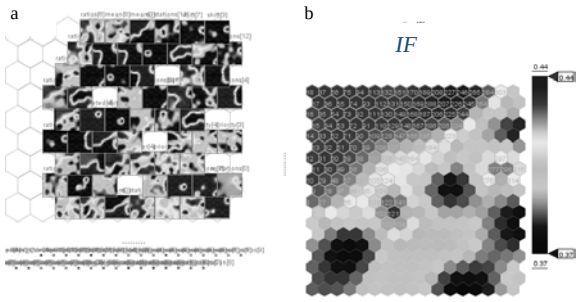


Fig. 8. (a) SOM components (b) SOM of *IF* component

The results from the second optimisation cycle of the clusters and from the methods SOM and MCDM are in table 3.
The preferred solution is from cluster 0 since it has the highest *IF* and throughput rate. Results from the weekly scheduling (the daily shift of trimming machine group has taken as an example) are in table 4.

Table 3. Production flow test case results.

| | | Simplex algorithm | | | | | |
|---|---|---|---|---|---|---|---|
| | Unit measur. | Clu_0 | Clu_1 | Clu_2 | Clu_3 | MCDM | SOM |
| completed product A | pieces | 1755 | 1755 | 1755 | 1755 | 1749 | 1719 |
| completed product B | pieces | 184 | 184 | 182 | 182 | 182 | 198 |
| completed product C | pieces | 558 | 558 | 558 | 558 | 558 | 558 |
| completed product D | pieces | 537 | 537 | 537 | 537 | 537 | 537 |
| saturation Selection | % | 53 | 53 | 53 | 53 | 53 | 53,02 |
| Saturation Washing | % | 66 | 66 | 66 | 66 | 66 | 65,86 |
| Total IF | / | 0.513 | 0.513 | 0.509 | 0.505 | 0,44 | 0,42 |
| Total standard dev. IF | / | 0.25 | 0.25 | 0.25 | 0.25 | 0,22 | 0,21 |

Table 4. Trimming machine weekly scheduling results

| | Unit measurement | MCDM |
|---|---|---|
| Trimming Monday-Shift | n° shifts/day | 1 |
| Trimming Tuesday-Shift | n° shifts/day | 1 |
| Trimming Wednesday-Shift | n° shifts/day | 1 |
| Trimming Thursday-Shift | n° shifts/day | 2 |
| Trimming Friday-Shift | n° shifts/day | 1 |
| completed product A | pieces | 131 |
| completed product B | pieces | 10 |
| completed product C | pieces | 22 |
| completed product D | pieces | 68 |
| saturation Selection | % | 68 |
| Saturation Washing | % | 56 |
| Total IF | / | 0.52 |
| total stand. Dev. IF | / | 0.22 |

## 5. Conclusions

The results the system gives are substantially better than before. It strengthens the idea that this method has great potential in improving a production system and decision making by using "what if" situations. The cycle time for each optimisation run varies between them. The first cycle of optimisation including the post-processing time lasted 3-5 days depending on the case study.

The second cycle of optimisation lasted only 2-3 hours. This underlines the fast speed of convergence of the simplex algorithm. Furthermore, for the production case study, the weekly scheduling optimisation and MCDM lasted, together, less than 24 hours. With such a short time, this method can be used not only as decision making but also for managing a manufacturing flow. It would simplify and make possible a dynamic scheduling of production launch in a short time. The applied methods reached the goal of the article.

From the two case studies it is possible to state that: the approach has the following advantages:

- Accurate: the model can give very precise results if the model is made properly. The accuracy of the system is given by how detailed the DES model is made with respect to reality. In any case, to avoid excessive level of detail within a model, it is necessary to build the DES model with the minimum level of detail that achieves its objectives.
- Robust: from the defined objectives, this approach gives the inputs that reaches the performances goals set. The input commands the simulation model and the objectives are strictly correlated to the output of the DES model (fig. 2) so, to have a robust system, the input and output must be correct. The model gives the user complete control over the system, solving the main problems and reaching the objectives and, thus, making the system effective
- Speed of convergence: instead of exploring all the possible solutions, the genetic algorithm will converge quickly to an optimal solution.
- Flexible: once the model is well defined, making variations is easy.

And the following disadvantages:

- Time consuming: The critical part of the work is preparing the WITNESS model: it takes from three to four days. The creation of the system and the search for the optimal solution is time consuming.
- Deep knowledge: the model creation and use of the approach requires profound knowledge of both the software and the factory production flow (industrial process).

## References


[1] Masao Yokoyama. Flow-shop Scheduling with Setup and Assembly Operations. Europ. J. of Operational Research 2008; 187:1184-1195.

[2] Gelders LF, Samdandam N. Four Simple Heuristicsfor Scheduling a Flowshop. Int. J. of Production Research 1978;16:221–231.

[3] Bolat A, Al-Harkan I, Al-Harbi B, Flow-shop Scheduling for Three Serial Stations with the Last two duplicate. Computers and Operations Research 2005;32:647-667.

[4] Yenisey M M, Yagmahan B. Multi-objective Permutation Flow Shop Scheduling Problem: Literature Review. Classification and Current Trends. Omega 2014;45:119–135.

[5] Ra P, Xavior A, A Genetic Algorithm Applied Heuristic to Minimize the Makespan in a Flow Shop. Proc.Eng. 2014;97:1735-1744.

[6] Liu Min, Wu Cheng. Genetic algorithms for the Optimal Common due date Assignment and the Optimal Scheduling Policy in Parallel Machine Earliness/Tardiness Scheduling Problems. Robotics and Computer-Integrated Manufacturing 2006;22:279-287.

[7] Ceran G, Mustafa K. Orhan YE. An Efficient Genetic Algorithm for Hybrid Flow-shop Scheduling with Multiprocessor Task Problems. Applied Soft Computing 2011;11:3056-306.

[8] Muthiah A, Rajkumar R. A Comparison of Artificial Bee Colony algorithm and Genetic Algorithm to Minimize the Makespan for Job Shop Scheduling. Proc. Engineering 2014;97:1745-1754.

[9] D'Addona, D., Teti, R., 2011, Queuing Network Modelling Techniques For Response Time Enhancement In Electronics Assembly, International Journal of Computer Aided Engineering and Technology (JICAET), DOI 10.1504, Vol. 3, Nos. 3/4: 399-413

[10] Bernidaki M, Mourtzis D, Doukas D. Simulation in Manufacturing Review and Challenges. Procedia CIRP 2014;25:213-229.

[11] Schmidt, J. William**,** Simulation and Analysis of Industrial Systems. R. D. Irwin, Homewood 1970.

[12] Ruiz R, Vazquez-Rodriguez JA. The Hybrid Flowshop Scheduling Problem. Europ. J. of Oper. Research 2010.

[13] Behnamian J, Zandieh M. Earliness and Tardiness Minimizing on a Realistic Hybrid Flowshop Scheduling with Learning Effect by Advanced Metaheuristic. Arabian Journal for Science and Engineering 2013; 38, Issue 5:1229-1242.

[14] Ling Xu, Jian-Bo Yang. Introduction to Multi-Criteria Decision Making and the Evidential Reasoning Approach. University of Manchester Institute of Science and Technology 2001;3-4.

[15] Konak A, Coit DW, Smith AE. Multi-objective optimization using genetic algorithms: A tutorial. Reliability Engineering & System Safety 2006;91, Issue 9:992–1007.

[16] Hwang Ching-Lai, Md Masud AS. Multiple objective decision making, methods and applications: a state-of-the-art survey. Springer-Verlag.1979; Retrieved 29 May 2012.

[17] Rudin W. Principles of Mathematical Analysis. (Third Edition*)*; McGraw-Hill, New York. 1976

[18] Pediroda V, Poloni C. Approximation Methods and Self Organizing Map Techinques for Mdo Problems. Problem of Visualisation in N-Dimensional Space (SOM) 2015; 19-20.

[19] Metternich J, Bollhoff J, Seifermann S, Beck S. Volume and Mix Flexibility Evaluation of Lean Production Systems. Procedia CIRP 2013;9:79-84.

[20] Allahverdi A, Gupta JND, Aldowaisan T. A Review of Scheduling Research Involving Setup Considerations. Omega, Int. J. Mgmt Sci. 1999; 27:219-239.

[21] Qi Hao, Shen W. Implementing a Hybrid Simulation Model for a Kanban-based Material Handling System. Robotics and Computer-Integrated Manufacturing 2008;24:635-646.

[22] Poloni C, Pediroda V. GA coupled with computationally expensive simulations tools to improve efficiency. Genetic Algorithms and Evolution Strategies. Engineering and Computer Science, John Wiley and Sons, England; 1997, p. 267–288.

[23] Goldratt EM, Cox J. *The Goal.* The North River Press; Great Barrington, Mass. 1992.