Application of Optimization Techniques to Support Decision-Making Processes Via The MSM

Beatriz Nunes Gonçalves  
beatriz.n.goncalves@tecnico.ulisboa.pt  
Instituto Superior Técnico, Universidade de Lisboa, Lisboa, Portugal  
November 2017

Abstract—In the past decades, a generalised awareness and concern for sustainability issues has been gaining increasing relevance. Governments and industries around the globe are focusing not only on their environmental impact and cost competitiveness but also on efficiently managing their resources. Therefore, some of the most popular strategies adopted by different industries are the increase of productivity and waste reduction.

In this context, and with the goal of promoting European sustainable industries, the MAESTRI project is born. This project comprises a methodology that aims to evaluate the performance of productive systems in terms of their flow and resources - the Multi-Layer Stream Mapping (MSM).

The main contribution of this master thesis is the application of metrics defined by the MSM as decision variables in different search techniques, employed in an industrial context. Therefore, the optimization process is helpful for strategic and informed decision-making right before shop-floor implementation.

Firstly, the production system must be modelled considering the constraints and limitations present in the dynamics of real-life situations. Secondly, the development of the MSM efficiency board, which is based on post-simulation variables, allows to intuitively identify waste and limitations of the productive system relative to the final products that are being studied.

Thus, besides the heuristics applied to the problem, the solutions provided by the metaheuristic were also analysed. The results were positive since the genetic algorithm can improve the MSM metrics and reduce inefficiencies in the production system.

Therefore, several scenarios depicting dilemma situations can be idealised.

Index Terms—MAESTRI, Multi-Layer Stream Mapping, Discrete Event Simulation, Job Shop, Optimization, Metaheuristics.

I. INTRODUCTION

Due to a colossal competitive pressure in an increasingly demanding market, manufacturing industries are facing an ever-growing international rivalry. With rigorous customer requirements, several studies emerged relating the overall production system efficiency with the proper management of both operations and resources. Those facts must lead to transformations in terms of quality, reliability and productivity requirements [1].

This exposed scenario led to investigation studies to be carried out towards the emergence of monitoring the production systems’ performance regarding flow and resources usage.

Moreover, there is an open-ended European research project that aims to assist on decision-making processes. In fact, this work was developed under the scope of this project - MAESTRI, that promotes an innovative approach within many industries to oppose these vicissitudes, based on principles such as Lean thinking and ways to evaluate the efficiency of process industries [2].

In this sense, this dissertation presents a novel methodology to assess optimized parameters to a real production system. As an optimization problem, characterized by the intervention of multiple variables, the main contribution of this work comprehends the application of optimization methods to support the decision-making process based on the indicators that best suit each product’s MSM.

Therefore, by applying both heuristics and metaheuristics methods whose results are mostly analysed and compared, it is possible to then consider different scenarios that bring out some trade-offs with them. To help in the decision-making process, those results are presented after discussing some meaningful cost functions.

A. Motivation

Within manufacturing industries, the need for tracking their systems’ performance is becoming trendier as a way of achieving improvements. Therefore, they can reach a comfortable position in their market. However, the main issue of coupling the systems’ efficiency with the subsequent economic growth is that engineers come across with many trade-offs [3].

Considering the urgent need for efficient solutions regarding the industries reality and resorting to Operational Research (OR) techniques, the so-called metaheuristics family is amongst the most promising and successful optimization procedures. This interest in the metaheuristics domain has an explanation: it provides solutions in a legitimate time frame for solving hard and complex problems in science and engineering [4].

II. RESEARCH ON PERFORMANCE ASSESSMENT

To reach high competitive levels that allow companies to endure, they need to adapt their production tactics to equal or even exceed the market’s competition [5]. In this context, current industries are engaged in simultaneously reducing different waste sources and increasing overall productivity, therefore enhancing the value of their products.

With all this in mind, industries have to trace objectives that fulfil their economic goals in a sustainable manner. Those realistic trade-offs between business and performance concerns are highlighted by an ongoing European project named MAESTRI that, as [6] states, “aims to encourage a culture of improvement within manufacturing and process industries by assisting the decision-making process, supporting
the development of improvement strategies and helping to define the priorities to improve the company’s environmental and economic performance”.

A. Operational efficiency requirement

The need for operational efficiency monitoring comprises, in its own definition, the delivery of products and services in the most cost effective manner without sacrificing their quality [7]. Hence, its gist concerns the requirement of “doing things right while doing the right thing”. Operational efficiency is often achieved by adjusting core processes to respond more effectively with less waste sources.

1) Operational waste management: A company needs to minimize waste while boosting the resources that contribute most to its success and utilizing the best of its workforce, technology and business processes to conquer good operational efficiency results. Along with this, material flows are still largely unmonitored when compared to the financial ones, and it is necessary to contradict this paradigm, especially when they become waste [8].

Then, a powerful waste’s management plan is decisive when the final goal is to accomplish high efficiency. This can be done by reducing the Non-Value Added (NVA) activities performed, which are commonly referred to as waste, in favour of the Value-added (VA) ones for which the customer is willing to pay for.

2) Lean manufacturing: Lean manufacturing came to completely revolutionize manufacturing activities by changing how directors supervise processes, how managers administrate and how employees operate on the shop-floor [9].

Considering that Lean manufacturing focuses mainly on assuring value for the customer by eliminating waste in the manufacturing industry processes, multiple inefficiencies and waste activities must be eliminated.

Also, it is important to understand the different Lean principles, which are in the origin of tools that allow for the accomplishment of eliminating waste sources:

- Specify value;
- Map the value stream;
- Establish flow;
- Implement pull production;
- Work to perfection.

By following the five principles of the Lean thinking, an organization must be able to maintain or improve its high level of service without compromising its flexibility capability [10].

In fact, manufacturing processes can be diagnosed with several Lean tools including the Value Stream Mapping (VSM), exploited in the second Lean principle, which graphically depicts the current level of leanness of a system.

One of the major goals of the VSM Lean tool is to determine, and clearly distinguish, the productive and non-productive time during the product manufacturing or during a service provision [3], providing this way a powerful tool to assist on industrial decisions. As a result, the VSM proposes a future state to the analysed area in which all the detected inefficiencies should be improved according to Lean principles.

Lean tools and techniques are simple to understand and can, therefore, be used by different elements of the company. Those tools can be applied in the production system’s diagnose, to identify the different phases of the system, to characterize numerous inefficiencies or to support improvement solutions [11].

B. Sustainable production systems - a global trend

Intense industrial activity has contributed to the growth of environmental concerns on a global level and, as the world’s population and standard of living increases, some old solutions to industrial pollution and every day waste no longer work [12].

Based on a holistic approach, companies are struggling to develop more resource and energy efficient processes, utilize waste streams and improve sustainable recycling, modelling and assessing all the interacting value chains [2].

1) Sustainability: Working on a sustainability basis comprehends the creation of products that on the one hand generate profit and on the other hand minimize environmental impact and saves resources.

Manufacturing is the process of transforming inputs like material, personnel and energy into valuable outputs, designated by products, often together with undesirable outputs, such as waste and emissions.

With economic aspects being clearly spotlighted, factories are associated with diverse negative environmental and social impact [2]. Trying to contradict this reality, sustainable manufacturing practices are gradually becoming a more and more vital component used by companies which use them as a key ingredient to increase business performance and competitiveness [13], [14].

2) The MSM approach: The MSM was developed, between 2012 and 2013, in order to create a tool able to perform an overall efficiency assessment of production systems [3], while evaluating the productivity and efficiency of resource utilization, waste and other process domain variables.

The MSM focuses on the diagnostic of each product and bets on an easy interpretation and direct understanding of those results to quickly identify critical aspects and inefficiencies of the system, due to its intuitive visual layout [10], [15].

Nonetheless, the Lean tool is intended to be used, not only for analytical evaluation, but also to support the decision-making process, namely for online systems monitoring or greenfield design [3], related with:

- Identification of the most critical resource or process parameters;
- Recognition and quantification of inefficiencies of a given production system and unit process;
- Assessment of both resource and operational efficiency and overall production system performance and costs;
- Implementation of improvement and optimization actions;
- Evaluation of efficiency progress, promoting continuously improved sustainability within organizations.
Even though VSM is evidently a powerful tool, it has some limitations that mostly relate to the analysis of multiple flows. Therefore, a new MAESTRI inspired tool called MSM was born. It intends to properly evaluate the efficiency of the different steps associated with the value chain by taking into consideration more variables other than just time, as expressed in Figure 1.

![Fig. 1: VSM gives origin to MSM. Adapted from [3].](image)

Nevertheless, the MSM only diagnosis and assesses information, as the traditional VSM. Thereupon, an expert has to analyse them and support improvement suggestions on presented metrics.

3) **Structure description:** The MSM outlines efficiencies’ performances and lays them out in a simple manner through a visual platform to simplify top/middle management understanding performance indicators, as well as their suitability for decision-making. This leads to a visual management of the presented metrics that results in a sustained decision process.

The MSM methodology resembles a matrix, such as the one depicted in Figure 2, where rows are associated with the different chosen indicators to evaluate the system, and columns illustrate the different steps of the production system, designated by processing units.

The MSM methodology promotes an extensive comprehension about the current system performance, regarding flow and resources. Each process has an associated performance, which is calculated by means of Equation 1.

\[
\phi = \frac{VA \text{ fraction}}{VA \text{ fraction} + NVA \text{ fraction}}
\]

Having all this in mind, the main purpose of this thesis is introduced, as it intends to is not only to use the MSM as a pure diagnosis tool to detect inefficiencies after the production activity, but also to set up different scenarios and do this diagnosis in a preventive way.

4) **The birth of the MSM 2.0:** A new approach to the MSM methodology was proposed by [10] and asserts that NVA phases like setup, transports, storages and waiting times are essential activities to study since they consume resources like time, energy or materials, and consequently have costs to the company and influence on the system performance. Therefore, this new potentiality is associated with MSM 2.0 and integrates the waste activities in the original methodology, making it possible to obtain entire product flows [10], [11].

The author of the MSM 2.0 asserts that the metric proposed in Equation 1 can now be calculated by two different formulas, depending on whether the resulting performance indicator should be either maximized (Equation 2) or minimized (Equation 3). Thus, the direction of improvement for each of the indicators depends on the strategy and goals of the company [10].

\[
\phi = \frac{\text{Total value}}{\text{Designed value}}
\]

\[
\phi = \frac{\text{Designed value}}{\text{Total value}}
\]

The so called designed value is defined by the company according not only to its goals but also to its operational capabilities, and consequently its targets should be as realistic as possible. On the other hand, the total value is dictated by both designed and waste values, in other words it assigns the current measured value for the indicator [10].

The following project will be focused on the MSM 2.0 methodology.

III. PROBLEM STATEMENT: A REAL CASE STUDY

The present work consists, in first instance, of applying the MSM 2.0 methodology to one of the MAESTRI’s partners which has different types of machining processes [16]. The MSM 2.0 tool is usually applied in the production system diagnostic after conception of final products, and it gives an idea on how processes and their related activities can be improved to remove inefficiencies.

A. **The company**

This dissertation is supported by a practical role which was assured in the portuguese privately owned company, MCG mind for metal.

MCG is a metal component and assembly manufacturer that already counts on around sixty years of experience. This familiar firm is fully established in Carregado, Portugal, with five different manufacturing business units that employ about four hundred workers with various specializations [17].

All data was gathered by visual observation, time measurements or even interviews to operators, making sure that the usual work and the employees’ jobs were not destabilized. This contributed to the production system model creation and
its consequent validation, to ensure that it represents the real system behaviour.

B. Production system characterization

This type of manufacturing process is designated by job shop production, which is based on the process outline itself. In other words, the similar operations are aggregated in unit processes, and products go through a specific sequence within each unit process, as described in Figure 3.

In MCG, not only resources management a hard task, paying attention to the Bill of Materials (BOM) of each end product is also required. In fact, sub-assembly operations are performed in different unit processes, such as in the manual welding or in the kits sections. This way, it can be considered an assembly job shop scenario.

Also, this company has at its disposal both manually operated machines (controlled or supervised by a human worker) and semi-automated machines (that perform a portion of the work cycle under program control and the remaining work under the handling of a worker).

C. Processes description

The MAESTRI project reported the most significant bottlenecks of the MCG's production system. The bending and manual welding processing units are the ones that reveal the worst repeatability, which generate some relevant reworking hours. Moreover, the raw materials warehouse management and the Work in Process (WIP) flow also revealed poor repeatability [18].

Taking into consideration that the complete production system is highly complex and detailed, this subsection focus its attention mainly on the bending and manual welding unit processes. This means that this work also brings some considerations about the NVA kits unit since it is the connecting block between those two main processes, as illustrated in Figure 4.

Orders planning. This delineates exactly which processes the Manufacturing order (OF) must pass through as well as the times of each operation to be performed. Hence, it also creates a correspondence between the BOM and each one of those OFs.

Bending. This workstation configures, by the action of a pressure force impelled by a machine, the required parts into its final desired shape. This section has four different machines.

Manual welding. This unit process joins parts of a same sub-assembly. But in this work, it will be considered that this generates the final products. This section has six different machines, four that work with MIG/MAG techniques and two that follow the TIG procedure.

Kits. This section only generates WIP since the parts produced in the bending process are stored here to make a kit. The kit contains parts of a sub-assembly. In this work, a kit is considered to be the final product.

In order to fully evaluate the production system, the activities performed in each one of the unit processes above stated, will be integrated in the production system analysis whether they are NVA tasks or not. In the system’s modelling, each process is divided into activities:

- **Operation.** Time needed to perform the bending action or the welding itself;
- **Setup.** It is a NVA pure period that is required to prepare a machine, tools or material necessary for it to be ready to accept a new job. Regarding the sections analysed in this work, this activity is part of both the bending and manual welding processes;
- **Waiting period.** Each workstation has a place, marked on the floor, where parts wait to go to a machine (the IN area) or to get out of the processing section (the OUT area). However, while in the bending and manual welding processes the waiting is part of the whole, in the kits process the waiting period consists on the whole time spent in the activity.

D. Indicators

With the system boundaries identification comes the selection of the most suitable indicators for the MCG’s production system. This selection was made by taking into account the representativeness of the suggested indicators to the case study.

The extended MSM only represents the metrics for the final products. In this case, the final products are considered to be the result of the manual welding unit process. Having this said, waste value of the extended MSM is the metric’s sum values of the bending’s OFs. It is the reason why an extended MSM of a final product also appears with the bending process characterization. Similarly, the extended MSM of the kits section consider the metrics of bending OFs that are waiting for others to produce a kit.
1) Flow indicators: Time. An arbitrary time is planned to a specific job according to the company’s cadence and production level, and it is assigned only to the operation task and excludes setup and storage times. So, the designated time is considered a VA activity. Also, it is assumed to be the shortest possible time regarding the all planned times for each machine on disposal.

The indicator that refers to time efficiency sums up the ratio, expressed in Equation 4, between this designated time and the time that the part takes to be produced in reality.

$$\phi_{\text{time}} = \frac{\text{time planned} [\text{sec}]}{\text{total time} [\text{sec}]}$$  

(4)

Time in equipments. The indicator expressed by Equation 5 has only meaning in the operation and the setup phases, as long as parts only spend time in a machine during their manufacture.

$$\phi_{\text{time in equipments}} = \frac{\text{time planned for machine } m [\text{sec}]}{\text{total time in machine } m [\text{sec}]}$$  

(5)

2) Resources indicators: Equipment power consumption. It refers to the electrical energy over time supplied to operate an electrical machine (see Equation 6). It is important to take into account two different power values, the one that is associated with a machine performing an activity and the one that is the residual power that the machine has when idle.

$$\phi_{\text{pc}} = \frac{\text{machine power} [\text{kWh}] \times \text{time planned in machine} [\text{h}]}{\text{total power consumption in machine} [\text{kWh}]}$$  

(6)

Workers usage. The rate of operators effectively contributing with VA activities is given by the indicator in Equation 7.

$$\phi_{\text{workers usage}} = \frac{\text{workers needed} \times \text{time planned} [\text{s}]}{\text{total workers scheduled} \times \text{total time} [\text{s}]}$$  

(7)

IV. Production System’s Model

Simulation-based scheduling prefers a simulation model of the facility to the detriment of a set of mathematical constraints that define it. This approach allows the implementation “as-is” on the shop-floor without adjustments, avoiding non-optimal schedule decisions when infeasible solutions are created [19]. In fact, it also requires that all the data is fully known and deterministic.

A. Theoretical approach

Firstly, a generic scheduling problem should be formalised before it is effectively modelled and analysed. In Figure 5, by resorting to the use of formal methods based on timed Petri nets, the system modelling and consequent analysis of temporal behaviour can be easily achieved.

Gray arrows represent different possibilities of routing an OF inside the manufacturing system. It all starts by simultaneously generating different OFs, at simulation start. Lighter gray squares are decision phases that establish at least two different possible routes.

Also, a simplification of the reality intends to promote faster understanding. This procedure allows the study to focus on which is really important to understand. The enumeration of some assumed simplifications and constraints make the model development easier to perceive [20]:

- There is routing flexibility since operations can be processed on more than one machine, within the same process (in case of bending) or within the same type of process (in welding);
- Preemption or job cancellations are not considered;
- A machine can only process one job at a time. While in the bending process, a job can be performed by more than one employee, in the welding process only one is needed;
- Each bending machine has its own planned setup and operation times, because they are different in reality. If similar parts pass one after another, setup is only performed once;
- In the welding process, each type of solder technique has the same planned times;
- In the kits section there are always three employees continuously working;
- Breakdowns are not contemplated in this study;
- All jobs are inspected a priori i.e., no defective part is advised;
- Jobs are not independent because it is an assembly job shop, and therefore final products depend on the parts that constitute them. The kits section is where the OFs assembly is made;
• Order volumes are known since the planning generates the necessary OFs;
• There is no flexibility associated with setup or operation times of a same OF. Although the model is prepared for this situation, it was impossible to collect this kind of data in MCG. This will directly impact both in the setup and operation efficiencies that will be in any case of maximum value;
• Transport times between different processes are considered null. This means that it will not be registered any time in the bending OUT section since all parts proceed directly to the kits section;
• Products originated in the welding process are considered to be the final products of the manufacturing system. This information will affect the time parts spend in the welding OUT section, it will be always null and its efficiency is maximum.

B. Practical description

The MCG’s production system model was developed resorting to the software SimEvents, and was inspired by scheduling practices.

In the MCG’s production system model, a production plan that includes the OFs waiting list is assumed to be the entity generator source. In detail, entities are OFs that the manufacturing system has not yet started. Entities are generated as the simulation starts. By reading an Excel file with the production plan’s variables for each OF, it inputs information into the model. Among various other attributes, entities must record the OF number, employees that will be needed to perform the operation, the assigned machine to each job and different planned times depending on the machine.

Also, different resources have diverse capacities that are assigned to the model based on another Excel file. This way of reading information through Excel was considered due to the current way of working in the MCG, i.e., they have all informations in Excel files.

V. Optimization technique selection

After having the problem translated into a model, and being able to simulate scenarios, a computer-based procedure to find promising solutions is needed.

Subsequently, for most real-world problems there are no efficient algorithms that allow NP-hard optimization. They require exponential time to be solved optimality. In fact, according to [21], job shop scheduling problems are NP-complete problems due to the exponential growing search space in possible resources and goals combination. The case study along referred in this thesis, as it is even more constrained, requires high computational times.

A. The world of metaheuristics

One of the recent particularly exciting developments in OR has been the rapid progress in developing very effective heuristic algorithms. OR teams frequently use them to quickly find a good suboptimal solution since they do not guarantee an optimal one [22].

Metaheuristics are not only as effective in small size problems as heuristics are, but also can tackle larger sized problems by delivering satisfactory solutions in reasonable time.

Some of the most widely types of metaheuristics applied are tabu search (TS), simulated annealing (SA), ant colony optimization (ACO) and Genetic Algorithm (GA) [22]. Choosing the right metaheuristic is not a straightforward decision, and generally calls upon the know-how of the decision-maker, rather than the faithful application of well laid down rules [23].

B. Review on similar problems formulations

The inherent complexity of the job shop scheduling problem has been so dynamic that there are no single strategy that can be applied to deal with all real situations [21]. The ever-changing shop floor environment makes the problems even more difficult to solve.

Relatively much less effort has been put on assembly job shop production problems with BOM.

As far as assembly job shop problems are concerned, earlier contributions are due to [24] and [25]. The goal of those works is to improve the products performance as well as reducing WIP inventory, by employing a technique based on Lagrangian relaxation. Moreover, [24] proposes a heuristic method for minimizing the production time of jobs involving both machining and assembly operations in a production shop. Recently, [26] analysed real-life requirements of an assembly job shop problem and tried to solve it by mean of Petri nets. Then, the authors use the Branch and Bound heuristic procedure to solve the problem. However, there are some papers, such as [27], that develop themselves new heuristics to deal with very specific assembly job shop problems.

Notwithstanding, most of those examples have a similar final objective, as far as they are concerned with deadlines fulfilment and makespan minimization. However, the goal of this thesis exceeds all these aspirations since it computes values of indicators that in spite of depending on system’ behaviour, are not obtained directly.

In practice, a vector inspired by [28] was developed to feed the model with the respective machines allocation, as explained in the previous chapter. Discrete variables encode the solution for the scheduling problem this thesis aims to solve, as clarified in Figure 6.

Fig. 6: Vector schema with assigned machines to each OF.

The vector represented can be subdivided into two different sections that correspond to each process. Then, each entry of the vector refers to the machine allocated to a OF. In other words, Figure 6 suggests that the first OF goes to machine 2.
in the bending process and to machine 3 in the welding one. Similarly, the second listed OF proceeds to machine 1 in both bending and welding processes, and so on to other OFs.

C. Heuristic approaches

A solution to this problem can be quickly found by using ad hoc techniques or by following well-known methods that have produced efficient solutions to similar problems [29].

Traditional approaches to scheduling problems depend heavily on dispatching rules and knowledge-based systems. The disadvantage with such dispatching rules is that there is no single rule that will be effective for all production conditions, and manual selection or updating is required when using rules [21].

Regarding the assembly job shop problematic, some research and heuristics development was made in this issue. As an example, [30] focus its attention in two working parallel machines and makes use of the First Fit Decreasing heuristic. Additionally, the journal article [31] applies some heuristics procedures like First Fit and Decreasing Order to a problem in which machines are stopped for some interval times. In both cases, scheduling problems are similarly to the bin packing problematic where those heuristics are very useful. Having this in account, and due to a completely different case study constraints and formulation, some heuristics and algorithms were also developed.

The most important part of any heuristic, in this context, is to order the information coming from the Excel, i.e., the order of OFs in the production plan. To this end, three different approaches are used: ordering by batches; by increasing demanding quantity of each OF; random order. Then, to assign each job to a machine, first fit heuristic and random assigning are used.

D. Genetic algorithm

Most of studies about metaheuristics for job shop problems are focused on population based metaheuristics [27]. The main advantage of a population-based method against a single solution metaheuristic resides in the definition itself - in the final state, many (near) optimal solutions can be achieved. Moreover, there is a search space with many local optima for population-based methods, good solutions with high probability will not be lost. Thus, new candidate solutions with special characteristics will be generated from other solutions in the collection [32].

The GA is arguably the most well-known and most used evolutionary computation technique [33]. The discrete variable handling is remarkably important because this case study is a combinatorial problem, in which the aim is to optimize the machine allocation to each job, as explained by means of Figure 6.

A genetic algorithm is a stochastic method that uses evolutionary concepts to find better solutions in a search space. It uses a population of solutions, that is changed to create the next population, also called offspring. As previously mentioned, GA has three main steps: selection, responsible for picking up solutions and creating a parent population; crossover, which combines the parent population and creates offspring; and mutation, which randomly changes individuals in hope of finding good traits. Figure 7 illustrates these steps, in a cycle. Those operators are regulated by parameters that tune the intensity of their produced effect.

![Fig. 7: Generic GA’s operators procedure.](image)

The native `ga` function of MatLab was used, changing some parameters such as population size, number of iterations or genetic operators parameters. Foremost, randomly generated solutions constitute the initial population.

Random selection also occurs to pick solutions to go through crossover and mutation. The specific operator chosen is uniform crossover, illustrated in Figure 8, which randomly selects one vector entry from one of the parents, to all entries. A fixed probability of 50% is used, meaning both parents contribute to the same amount of vector entries.

![Fig. 8: Crossover operation schema](image)

The mutation genetic operator provides diversity and enables the GA to search a broader space. It starts also by randomly selecting an individual to change it. Uniform mutation was chosen, which randomly selects a gene and replaces it by an uniform random value between the lower and upper bound of the solution vector, as exemplified in Figure 9.

![Fig. 9: Mutation operation schema](image)

Hence, a maximum number of generations was used as the stopping criteria.

Resorting to the GA corresponds to the phase of assigning machines to each one of the OFs in the production plan. But before, some way of ordering the production plan can be applied.
VI. ACQUIRED RESULTS

The function defined in Equation 8 tries to maximize the time indicator efficiency (in Equation 4) as an average of every OFs of the manufacturing plan. In the defined cost function, $\phi_{time}B_{IN}$ represents the average efficiency for the bending IN section, and other coefficients’ meanings are inferred by analogy.

$$F = 0.2 \times ((1 - \phi_{time}B_{IN}) + (1 - \phi_{time}B_{OUT}) + (1 - \phi_{time}K) + (1 - \phi_{time}W_{IN}) + (1 - \phi_{time}W_{OUT}))$$  \hspace{1cm} (8)

A. Heuristics

The fitness values of the cost function, Equation 8, are plotted in Figure 10 which shows a wide range of final values to the assigned cost function, allowing a variance to be visualized.

$$\begin{array}{c|c}
\text{Batches FF} & F = 0.4796 \\
\text{Batches RM} & F = 0.5119 \\
\text{Quantity FF} & F = 0.5537 \\
\text{Quantity RM} & F = 0.4361 \\
\text{Random FF} & F = 0.4765 \\
\text{Random RM} & F = 0.4363 \\
\end{array}$$

B. Genetic algorithm strategy

The same analysis is now made using the GA algorithm. The model input is the manufacturing plan that was also imposed to the system in the best heuristic registered, and consists of ordering the OFs in a decreasing way regarding the quantity to be produced.

The optimisation procedure was carried out having 80 generations composed of 20 individuals each. Moreover, the mutation and crossover probabilities are of 20% and 80%, respectively. In this case, the elite corresponds to 10% of the analysed population.

In Figure 12 is possible to verify the metaheuristics power, but in particular of the GA. The outlined behaviour of the computed cost function value reveals that metaheuristics can overcome local optimal values. In other words, the stair behaviour is typical when the search for a sub-optimal solution is performed with metaheuristics techniques.

Besides this, the optimization of the scheduling process to improve some MSM metrics brings out a more sophisticated problem. Instead of optimizing the system only in terms of the makespan metric as classical job shop problems do, it resorts to many variables based on time and computes the indicators that comprise the cost function. So that, it is not easy to see improvements in this kind of plots with naked eyes.

Table I sums up the results for different analysed heuristics.

C. Comparison between the applied heuristics and the GA

To establish the algorithms comparison, only the best performed heuristic and the GA methods are taking into account.
To make this analysis in the light of the MSM 2.0 methodology, its metrics’ overall results are set side by side. Besides the MSM only refers to one final product, to make a global comparison between both the heuristics and the GA approaches, an MSM tool that represents the average efficiency that takes into account all final products has to be enunciated. In both Figure 13 and Figure 14, the average result of the final products’ MSMs are outlined. The effects on the indicators values are more perceptible in the rightmost column.

Fig. 13: Final MSM that results from the best heuristic.

Finally, and as expected, the MSM metrics improved as the cost function value decrease. It proves another time that the GA approach is more effective than any heuristic.

D. Simulating scenarios

Besides the improvements in efficiency values, resorting to the GA also allows to improve MSM metrics regarding specific scenarios. Some real impasses that OR teams face are here mentioned and therefore analysed the possible direction that the company’s strategy should follow.

Specific process’ metrics improvement Suppose that a specific process should be improved since it is actually causing huge WIP quantities. Here it will be assumed that the bending process requires to be improved in detriment of other unit processes, but taking them also into account. Therefore, a new cost function is defined (Equation 9).

\[
F = 0.425 \times ((1 - \phi_{tune}B_{IN}) + (1 - \phi_{tune}B_{OUT})) + 0.005 \times ((1 - \phi_{tune}K) + (1 - \phi_{tune}W_{IN}) + (1 - \phi_{tune}W_{OUT}))
\]

(9)

The resulting MSM metrics are outlined in Figure 15. In this case, visual perception of the improvement is not instantaneous. However, regarding the bending unit process, some metrics were improved when comparing with the Figure 14.

Fig. 14: Final MSM that results from the best fitness value of the GA.

Fig. 15: Final MSM that results from the Equation 9 optimization.

It then proves that the cost function implementation is effective in optimizing the scheduling practice in order to improve the MSM metrics that respect to the bending process. Undoubtedly, the same purpose for the kits and manual welding processes would successfully reach better metrics for them.

The model outputs the best scheduling practice for both bending and welding processes (here it is only presented the first, see Figure 16) found by the cost function implementation.

Fig. 16: Solution to be implemented in the bending unit process, after optimization with the cost function in Equation 9.

Indeed, this solution surely is of hard real implementation for the most common cases because it evolves assigning batches in an uncontinuous manner to each machine. In this case study, it can be easily implemented to the company since MCG already instructs a team leader per unit process to distribute the WIP that each machine should perform.

VII. Conclusion

Initially, data collection was performed in loco to ensure that all production system’s characteristic and peculiarities
were taken into account during the problem statement. This
evolved several visits to MCG factory. The production system
to be optimized was defined and modeled resorting to a
tactical tool that aims to make it of easy understanding. That
tactical tool consists of Simulink’s discrete event simulation
toolbox. The model was then fine-tuned in order to represent
faithfully the real MCG production system.

Thereon, a comparison between classical heuristics and
metaheuristics was performed. The best performing heuristic,
which consisted of sorting OFs with decreasing quantities to
be produced and then randomly assigning them to machines,
and using GA as a metaheuristic example. Results showed that
GA outperformed the heuristics in all tests, not only being able
to optimize the MSM indicators globally but also offering the
opportunity to optimise specific products or processes simply
by modifying the fitness function.

The developed work revealed to be of great importance not
only for the MCG but also for the MAESTRI project.

The fact that this work brings novelty to the MSM 2.0
methodology’s applications, also means that it is an embryonic
work and a lot more can do in this direction.

Furthermore, the optimisation procedure can be done with
multi-objective techniques, instead of assigning weights to
each metric. This can be done using several conflictual MSM
metrics.

**REFERENCES**

and Operations Control in Modern Manufacturing,” in Proceedings of

Pawlik, K. A. Nagorny, G. A. Grolle, P. I. Brizzi, and A. F. Schneider,

[3] A. Baptista, E. Lourenço, E. Silva, S. Plebanek, E. Pawlik, and M. Gil,
2016.

from Design to Implementation. WILEY, 2009, ch. One, pp. 1–86.

Integration for Improving Performance on Manufacturing Industries,” Global

S. L. Plebanek, and E. I. Lezak, “MAESTRI platform usage scenarios,”


The report of the UCL Green Economy Policy Commission,” London’s
Global University, Tech. Rep.

has to Offer the Process Industries,” Glasgow: 7th World Congress of


ing production system: An extension to the inter-processes operations,”


tainable Manufacturing: an Improvement Methodology,” in Sustainable

formance Mediate on Lean Manufacturing Practices and Sustainability,”
Journal of Humanities, Language, Culture and Business, vol. 1, no. 2,

layer Stream Mapping to assess the overall efficiency and waste of a
production system : a case study from the plywood industry,”
http://dx.doi.org/10.1016/j.procir.2016.04.086

http://www.mcg.pt/


2015.

php

Job Shops Scheduling Problem,” Master thesis, University of Windsor,
2012.

LAB and GA to Solve Job Shop Manufacturing Scheduling Problems,”
Proceedings of the 5th WSEAS Int. Conf. on Signal Processing, no.

[22] F. Hillier and G. Lieberman, Introduction to Operations Research,

[23] A. Pétrowski, E. Taillard, and P. Siarry, Metaheuristics for Hard Opti-
mization, 2013.

[24] D. Cummings and M. Egbelu, “Minimizing production flow time in a

using an improved lagrangian relaxation technique,” IEEE T. Robotic.

assembly job shop with timed colored petri net,” Proc. ICSSSM 2010,

heuristic for large-scale assembly job shop scheduling problems with
bill of materials,” in Advances in Mathematics and Statistics Sciences,
pp. 216–223.

Algorithm for the Flexible Job-Shop Scheduling Problem,” in Computers
& Industrial Engineering, 2011.


the machine scheduling problem with job delivery coordination,”
Theoretical Computer Science, vol. 410, no. 27-29, pp. 2581–2591,

[31] C. Low, M. Ji, C.-j. Hsu, and C.-t. Su, “Minimizing the makespan in
a single machine scheduling problems with flexible and periodic
2009.04.014

Superior Técnico, 2016.

[33] I. Boussaïd, J. Lepagnot, and P. Siarry, “A survey on optimization
metaheuristics,” Information Sciences ELSEVIER, vol. 237, pp. 82–117,
2013.