Optimization for Sustainable Manufacturing
Application of Optimization Techniques to Foster Resource Efficiency

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Abstract: Resource efficiency assessment methods, along with eco-efficiency assessment methods are needed for various industrial sectors to support sustainable development, decision-making and evaluate efficiency performance. The combination of eco-efficiency with efficiency assessment allows to identify major inefficiencies and provides means to foster sustainability, through the efficient and effective material and energy use. Despite the available information for decision making, this proves to be a difficult task in the manufacturing industry, therefore, there is a real need to develop and use optimization techniques to enhance resource efficiency. In this context, and due to the lack of simple and integrated tools to assess and optimize resource efficiency, crossing the different environmental and economic aspects, arises the need to develop optimisations models, enabling support and optimize sustainable decision making process and identification of potential improvements. The optimisation method should provide robust knowledge to support decision-making, allow comparability of the results and consider a cost-saving approach to help set priorities. Moreover, the optimisation techniques should centre the process through design/configuration of the production system, without considering time, in order not to limit the physical agents.

1 INTRODUCTION

Sustainability assessment has become a rapidly developing topic with a growing number of concepts and tools being developed during the last decades. This has been particularly relevant for manufacturing industries, main consumers of natural resources (Garetti, 2012). Despite the fact that the concept of sustainability might be understood intuitively, yet to evaluate the sustainability of production systems is a complex task and not intuitive, which led industries to deviate from these kind of issues. Therefore, an accurate management of sustainability issues is proven to be essential to achieve continuous improvement, and became a fundamental principle for successful organisations.

Common decision support tools provide the ability to access the immediate state of the process and some add the capability of simulating different configurations. The concept of sustainable manufacturing comprehends a significant number of objectives. The most quoted definition is given by the U.S. Department of Commerce: sustainable manufacturing is “the creation of manufactured products that use processes that minimize negative environmental impacts, conserve energy and natural resources, are safe for employees, communities, and consumers and are economically sound” (U.S Department, 2014).

Thus, maximizing resources and energy efficiency, reducing environmental and social impacts and promoting the use of renewable technologies are all key objectives included in the concept of sustainable manufacturing (Kersten, 1999). While evaluating these parameters might appear simple, using them for decision making can be more difficult, as these objectives must meet requirements regarding the impacts on employee, community and especially on the economic aspects (Kulatunga, 2015). Combining this set of conditions

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lead to complex problems. Sustainable decision support tools and frameworks simplify the assessment by using a single value to identify the immediate state of the process and by using carefully chosen indicators to simplify and compare the information.

Simulation tools go a step further and add the possibility to foresee the outcome of possible improvements in the process. However, the quantification of those changes can be a difficult process. Thanks to the indicator based system used in decision support tools there is a common comparison element between the immediate assessment and the simulated scenario. According to (Sproedt 2015), the major shortcomings regarding the simulation for the environmental assessment of production systems are the following:

- Product specific allocation of resources is rarely provided
- Materials and direct emissions not considered
- No seamless integration of Life Cycle Assessment (LCA) evaluation
- Focus either on environmental or cost evaluation
- High efforts for data acquisition and modelling required
- Lack of methodical guidance for application
- Level of detail not sufficiently scalable

Yet, advances towards industry 4.0 and total control of manufacturing systems, will lead to a significant increase of available information. Industry 4.0 leverages on the concept of Internet-of-Things (IoT), which incorporates machine learning and big data technology, exploiting the sensor data, machine-to-machine (M2M) communication and automation technologies that have existed in industrial settings for years. Smart systems are better than humans in capturing and communicating data. This data can enable companies to detect inefficiencies and problems earlier, saving time and money and optimizing business intelligence efforts. This would be overwhelming without proper tools to assist the treatment of that data. Decision support tools and frameworks assist in simplifying the problem identification process and the comparison of different alternatives.

1.1 Objectives

The goal of this paper is to present an approach to improve the overall sustainability of manufacturing through the simulation and optimisation of resource efficiency and eco-efficiency performance.

The eco-efficiency assessment through simulation is a support to better understand the influence of any process parameter on the production system performance. This can be done by the solver, which introduces changes regarding the process parameters quantitative amount, and assessing the influence of these changes on the production system efficiency and/or eco-efficiency performance. As a consequence, participants are able to identify and select process parameters that should be targeted for the identification of improvement actions. Moreover, the solver will support the identification of the optimal scenario.

2 BACKGROUND

2.1 Efficiency Framework

The proposed Efficiency Framework, developed under the H2020 SPIRE Project MAESTRI, consists in the integration of two methodologies, namely eco-efficiency and efficiency assessment methods and Information and Communication Technology (ICT) tools. The eco-efficiency method is oriented for the evaluation and assessment of eco-efficiency performance, while the lean based efficiency method, is to assess overall efficiency performance.

The eco-efficiency approach, here considered, aims to promote continuous improvement and a more efficient use of resources and energy, by providing a set of indicators easy to understand/analyse. The goal is to assess eco-efficiency performance in order to support decision making and enable the maximization of product/processes value creation while minimizing environmental burdens. Therefore, the use of the eco-efficiency approach, which base concept is to measure the environmental and economic aspects of activities as sustainability aspects that evidence, for instance, more value from lower inputs of material and energy (Baptista 2016). The common expression for eco-efficiency is the ratio between value and environmental influence (see equation 1).

$$\text{Eco-Efficiency} = \frac{\text{Production or Service Value}}{\text{Environmental Influence}} \quad (1)$$

The resource efficiency assessment methodology, takes into account the base design elements from the Value Stream Mapping. Namely, by considering the value streams, in order to identify and quantify, at each stage of the process system, the "value added" (VA) and "non-value added" (NVA) actions, i.e. all types of waste and inefficiencies along the production system (Lourenço 2013). Therefore, the basic principle relates to Lean Principles via clear definition between value and waste (in the Lean

Principles context). The goal is to assess the overall performance, by taking into account the efficiency of each process parameter/variable (e.g. time, energy, water, raw material) associated to one or more processing units. Consequently, the approach will provide an efficiency analysis (see equation 2), which supports the decision making process and helps prioritize the implementation of improvement actions by identifying inefficiencies in a very direct manner.

$$\text{Efficiency} = \frac{\text{Value added (VA)}}{\text{Value added (VA)} + \text{Non-value added (NVA)}} \quad (2)$$

The outline of the Efficiency Framework, consists in the integration of eco-efficiency and efficiency methods through the mutual exchange of information, which corresponds to the central objective of the Efficiency Framework. Such integration strategy enables to obtain, besides the efficiency and eco-efficiency stand-alone, results to support decisions and new integrated results, namely the Total Efficiency Index (TEI) - obtained by combining normalized eco-efficiency results with efficiency results.

Regarding TEI, this index is calculated for each processing unit of the production system under analysis. In quantitative terms, the TEI is obtained by multiplying the normalized eco-efficiency and the efficiency assessment results. The logic behind this index is to combine two fundamental efficiency aspects, namely eco-efficiency, which considers the ecology and economy aspects, and resource and operational efficiency, which considers the NVA and VA activities aligned with the Lean Principles from Multi-layer Stream Mapping (MSM). Consequently, TEI main outcome relates with providing the ability of evaluating if eco-efficiency performance variation is due to higher or lower environmental influence, or due to higher or lower economic value.

In practice, this results from the distribution variance of TEI results that occur on two major axes: the efficiency and eco-efficiency. This distribution is presented in a graphical way in Figure 1. The main characteristics and insights related to the TEI results distribution is:

- Quadrant I - High efficiency and eco-efficiency performance.
- Quadrant II - Low efficiency and High eco-efficiency performance.
- Quadrant III - Low efficiency and eco-efficiency performance.
- Quadrant IV - High efficiency and low eco-efficiency performance.

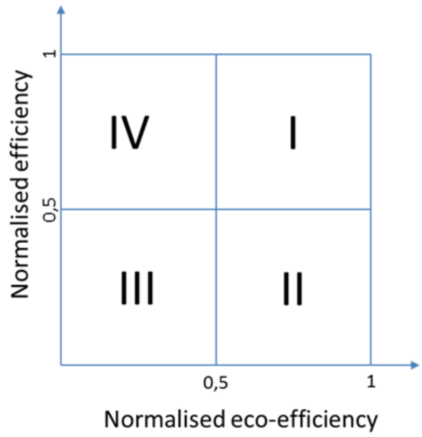

Figure 1: Theoretical distribution of TEI values.

2.2 Optimisation Problem

Problem arising in the industrial decision making process are a trade-off of conflicting objectives, e.g. identify which technology or processes sequence provides highest eco-efficiency and efficiency ratios, or identify the resource efficiency, environmental influence and costs of, for instance, different materials in order to identify the one that enables higher TEI. This kind of problem is commonly named Multi-objective Optimization Problem (MOP) and are mathematically represented by

$$\min\{F_{obj}(\bar{x})\} \quad (3)$$

where $\bar{x}$ is the array of process variable that influence the decision and $F_{obj}(\bar{x})$ represents the set of objective function taken into account.
MOP problem does not have a single solution but provide a set of solutions, named Pareto front, where different set of $\bar{x}$ have the same F_{obj}. Therefore, is not possible to have a global optimum but only near optimum solution are possible.

One way of representing $F_{obj}(\bar{x})$ is the weighted sum approach that is a linear relation of the single objective functions as follows:

$$F_{obj}(\bar{x}) = \sum_{i=o}^{N} a_i f_{obj-i}(\bar{x}) \quad (4)$$

where $f_{obj-i}(\bar{x})$ is the i-th objective function and a_i is the weight associated to f_{obj-i}. The single objective function is a relation between the process variable/parameters that can be controlled by the user and one of the objective. This relation can be of different form:

- Analytic - a mathematical representation of f_{obj-i} is available or can be retrieve through regression models.

- Black box - the system is too complex to be analytically modelled so the a f_{obj-i}.is established through the use of trained machine learning algorithm.

Many problem arising in this context are NonPolynomial-hard, meaning that they cannot be solved optimally in polynomial time. To solve large instances of this kind of problem the use of *heuristic* algorithm can provide approximate optimal solutions. They use some kind of knowledge in order to provide problem specific rules to explore the solution space, e.g. k-exchange neighbourhoods local search algorithm (Lin, 1973) (Helsgaun, 2000). A derived form of *heuristic* algorithm are the *metaheuristic* ones where a general applicable algorithm concept is used to define a *heuristic* method, e.g. Simulated Annealing (Kirkpatrick, 1984), Genetic Algorithm (Deb, 2002), Tabu Search, Particle Swarm (Shi, 2001) and Ant Colony (Dorigo, 2004).

Ant Colony Optimization (ACO) is a family of algorithm inspired by ants' behaviour and their way of communication when searching from food which allows them to find the shortest way between the colony and the food source.

Genetic Algorithm (GA) are inspired by the natural evolution process of a population. Each individual correspond to a point in the solution space and undergo to an evolution process. Individuals that have better results produce more offspring than others and genes from good individuals contribute to the generation of improved solution. Random mutation in the evolution process allow the algorithm to explore the solution space.

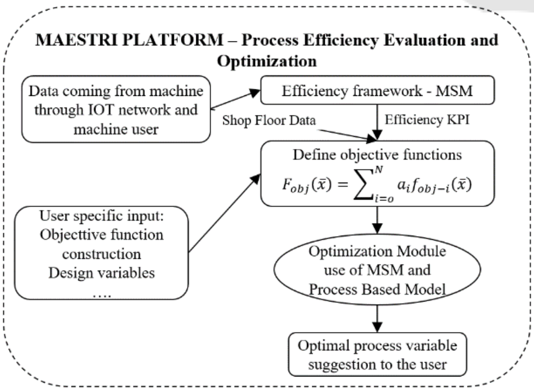

Figure 2: Optimization Module Architecture.

2.3 Use Case Example

The reference example used in the project to develop the efficiency framework and optimization module concept is the injection moulding. This production process is characterized by a variety of materials, shape and sizes that can be used by the same machine to produce from simple to complex products.

The use case example will consider the following variables:

- Cycle time measurement,
- Energy consumption per cycle,
- Material consumption per cycle,
- Parts produced per cycle,
- Number of Not-OK (NOK) parts per cycle.

The use case example considers that company established goals to continuously increase sustainability and resource efficiency. In order to assess efficiency and eco-efficiency performance based on energy consumption, material consumption and other key variables, like cycle-time. The use case considers that all necessary data on resources and materials costs, energy costs, as well as other cost factors related to process operation (machine operating costs, labour costs, parts selling price, etc.) can be retrieved via the IoT Platform, to enable calculation of eco-efficiency related Key Performance Indicators (KPIs).

The goal here is to better understand and optimise the interdependencies between process stages, both from technical and economic perspectives. For this reason, it is necessary to optimize energy and material consumption, in a manner that does not affect process productivity by creating problems on the other upstream and downstream process stages.

3 PROPOSED SOLUTION

Figure 2 shows the proposed methodology that will be implemented in the MAESTRI platform to support the decision making process in order to optimize the environmental impact and the overall efficiency. Figure 3 shows the MAESTRI platform architecture.

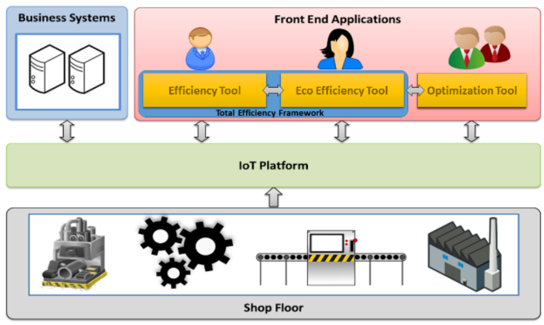

Figure 3: MAESTRI platform architecture.

The central element is an IoT platform, which facilitates the data transfer from machines, systems, and sensors at shop floor to end user software tools and applications at the industrial sites. Data coming from the IoT Platform and eco-efficiency KPI are used by the platform user to design specific objective function. The IoT Platform provides interoperable interconnection of appliances, devices, terminals, subsystems, and services. The platform has been designed according to the service-oriented architecture (SoA) approach where services are provided to the other components by loosely-coupled application components.

Each of the functional submodules of the architecture is explained in the following. The *Shop Floor* will usually be the place where the major part of the relevant data is being produced, e.g. material consumption in injection moulding machine. Device Connectors (DC) provide the means for devices to communicate with the rest of the framework regardless of the communication protocol it uses. DCs need to be developed specifically for each new device or protocol. *Business Systems* are the second type of data source. Enterprise Resource Planning (ERP) and Manufacturing Execution System (MES) systems can be connected to the IoT Platform in order to complement the data from shop floor. *Frontend Applications* represent all the end user software tools and services, which are the main data consumers from the point of view of the IoT Platform. These include mainly tools for eco-efficiency and process efficiency, which allow the overall assessment providing relevant KPIs. The optimization tool then finds the optimal solution, based on defined objective function and process based model, see section 3.1, with the result of optimizing the KPIs.

3.1 Modelling of the Process

The process modelling allows the optimization algorithms to iterate the influence of the design variables in the response function. Most of those relationships representing the influence of those variables are linear or can be simplified as linear (e.g. production rate vs. material consumption, parts per cycle vs cycle time per part, etc.). Nevertheless, the complexity increases when several linear correlations influencing the same process performance output are analysed simultaneously. One powerful approach is recommended to deal with this complexity – the process-based models (PBM) (Peças, 2013). The PBM comprises mathematical relations that bridge the design choices and the resources inventory from where the costs, environmental impact and value are calculated. PBM is composed by a process model and by an operations model. In the process model the relation between process variables and performance output are established and programmed. In the operations model the production context is defined, like number/type of machines, production time, operators use rate, etc. The PBM outputs are, in general, the time required to produce the parts, the material, energy and consumables consumed, as well as the number of tools, number of machine and other resources required (if applicable).

The aim of the intended analysis to be performed influences the PBM design (its extension in number of variables and outputs). Therefore, the eco-efficiency KPIs aimed to be accessed (optimized) should be defined in this phase. There are some almost obvious KPIs like the ratio between the product added-value and total environmental impact, parts produced and energy consumed or tool/system duration (in shots or parts produced during its life cycle) and its life cycle environmental influence (LCA results). For each specific analysis particular KPIs should be defined and the PBM must be designed to allow the output of time and resources consumed figures required for the KPIs calculations. Aiming to optimize a set of KPIs at the same time is not a simple task, since for the same process variables variation each KPI will vary in a distinct way, so metaheuristics methods abilities allow the identification of the most proper variable setting that maximizes performance.

3.2 Optimization Module

The process based model approach defined in the previous section can describe a relation between the input process variable $\bar{x}$ and the resulting process behaviour. With this and the tools implemented in the efficiency framework we can extract the TEI and other KPI that measure the ECO-efficiency of the process.

Figure 4 represents the optimization approach applied to the efficiency framework concepts. After the definition of the objective function composition that can be personalized following the specific project under study the optimization algorithm defines a new set of possible solution following its own characteristic strategy. The new set of solutions is evaluated through $F_{obj}(\bar{x})$ and if the value is minor than a user defined value the solution is accepted otherwise a new iteration of the optimization algorithm is run to find a new set of solutions. If the number of iteration is higher than a predefined maximum number defined by the user, the best solutions founded until that iteration are given to the user.

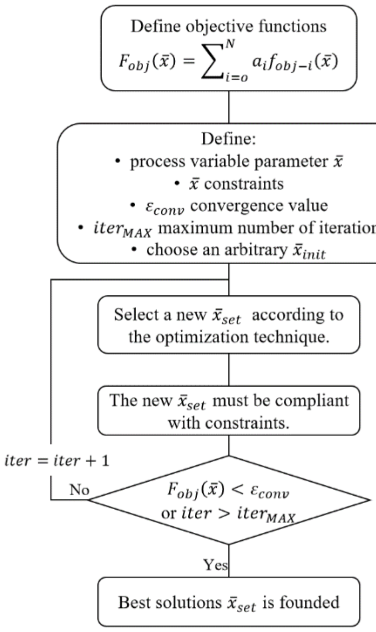

Figure 4: Optimization algorithm application schema.

In industrial process the number of parameters to be controlled can be very high so the selected optimization algorithm must be able to deal with a lot of input and to find the best solution of multiple objectives. In this application context metaheuristic algorithm, see section 2.2, are widely use (Satadru, 2015). The major drawback of metaheuristic algorithm is the fine tuning of the algorithm parameters to the specific problem but specific algorithm can be used to partially overcome this issue (Eiben, 2011).

The combination of different techniques, like Artificial Neural Network (ANN) and GA (Shen, 2007), is named Hybrid approach and can give good results especially in presence of non-linear relationship between the process parameter and the objective function.

Figure 5 shows the hybrid approach using ANN to simulate the process behaviour. The ANN must be trained during an initial phase and can be used in the iteration process to simulate the process. ANN can also be trained through simulation, that are time consuming, and continuously trained during the iterations, see (Shen, 2007). An example of application is the relation between the energy consumption and the process design variable. The black box approach through the use of ANN suite this kind of application due to the non-linear nature and difficulties in the evaluation with standard approaches.

3.3 Decision Support Capabilities

The connection of a highly integrated framework for both eco-efficiency and operations efficiency assessment, the MAESTRI Efficiency Framework, with a suitable optimization module and algorithms opens new vast opportunities towards providing solutions to complex problems in sustainability domain namely in industrial companies. Indeed, the capabilities of such rich methods and associated tools as the Efficiency Framework, besides their potential to individual analysis “what if improved scenarios creation” or even online monitoring, can become of more impact in the improvement strategies and deployment with the support of the adequate optimization technics. Providing only a selection of best available solutions the MAESTRI platform will help the user in the results selection and avoid wrong choices.

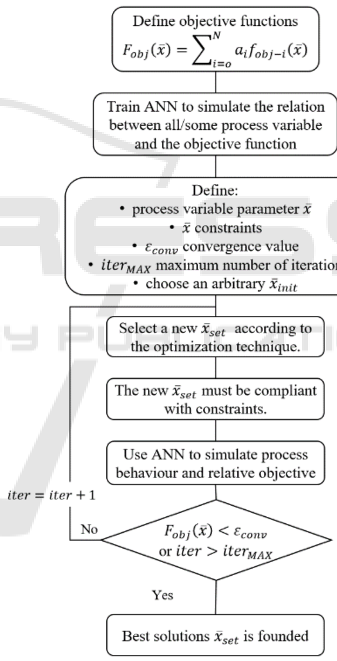

Figure 5: Optimization approach using ANN hybrid technique.

4 CONCLUSIONS

This work presents a first preposition towards an effective connection between a high level sustainability oriented tool, the Efficiency Framework, with the potential usefulness and industrial impact of a suitable optimization scheme. These connected tools will allow deeper analysis towards the optimization of resource efficiency, crossing the different environmental and economic aspects, enabling support and optimize sustainable decision making process and identification and quantification of potential improvements in the industrial processes. For that result, the optimisation methods should provide robust knowledge to support decision-making, allow comparability of the results and consider a cost-saving approach to help set priorities. Moreover, the optimisation techniques should centre the process through design/configuration of the production system, without considering time, in order not to limit the physical agents. The optimization task is enabled and facilitated leveraging a SOA IoT platform which provides services for efficiency and eco-efficiency assessment other than optimization.

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