POLITECNICO
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SCUOLA DI INGEGNERIA INDUSTRIALE
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EXECUTIVE SUMMARY OF THE THESIS

DEVELOPMENT OF A METHODOLOGY FOR DESIGNING PRODUCTS FOR DE-MANUFACTURING EXPLOITING ARTIFICIAL INTELLIGENCE

TESI MAGISTRALE IN MANAGEMENT ENGINEERING – INGEGNERIA GESTIONALE

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ACADEMIC YEAR: 2020-2021

1. Introduction

Digitalization, product servitization, big data and machine learning are now part of the ordinary language when it comes to manufacturing industries. Unfortunately, these trends are not exploited for their whole potential and, too frequently, are not employed at all by companies. This work has the ambition to provide clear guidelines and a framework to help manufacturing companies exploiting data collection and analysis for accelerating and enabling the large-scale introduction of Circular Economy related strategies. Most of the issues and challenges affecting European manufacturers and customers, indeed, have the potential to be solved with the introduction of circular techniques such as Reuse, Repair, Remanufacturing and Recycling, as long as they are supported by an integrated transformation of the entire business.
The methodology presented in this work will deal with the strategic problems and implications of introducing AI and Machine learning in one of the most critical and relevant activity in a manufacturing company: product design, with a lifecycle perspective.

2. Context

The starting point is the consciousness about the need, at manufacturing industry level, to change perspective and to move to a more sustainable and efficient management of resources, mainly intended as time and materials. This is due to the combination of megatrends such as demographic growth and social change, emerging markets, climate change and scarcity of resources which lead to the need to revolutionize the way value is created.
Circular Economy approaches represent the path to be followed. [1] However, their complexity still has to be tackled with a systematic and structured method. Circular economy processes like re-manufacturing, disassembly and recycling are still far from being deployed at a large scale due to issues related to the inherent complexity of products and to the difficulties in managing and organizing the reverse chain and the collection of

returned products. These issues can be faced through the combination of different tools and strategies, which are reported in this work. Among all the complex products that are now present on the market, specific mention is done for Lithium-Ion battery packs for Electric Vehicles, due to their increasing importance in current and future scenarios and to the high complexity related to their end-of-life management. The key finding, and the starting point of the work, is the major role that the design of products has in determining the feasibility and the easiness of adoption of the circular economy techniques. [2] Product design strongly influences the ability of a product to be handled, disassembled, inspected, repaired, and remanufactured. For this reason, product design is the target of the developed methodology. The first strategy which is introduced in the work is the design for product lifecycle. Particular attention is posed on the dynamics linking product to processes and system, dealing to the need to strategically consider the re-definition of companies' processes and systems when acting on the product. Tools for achieving this goal are represented by the introduction of Artificial Intelligence technologies and in particular Machine Learning. Major issues in the adoption of this technology mostly regard the proper identification of needed data and their collection.
In current scenario, attempts of using machine learning for solving circular economy issues have been made but are still very far from being deployed. Also, they do not focus on the design of products, rather on specific operational issues, with a very poor level of integration.
On the other hand, new research are under development as concerns the introduction of machine learning in product design phase. Although they do not specifically target De-manufacturing purposes, an interesting example of such kind of implementation is provided in [3] and [4].
In this variegated and challenging context, this work has the aim to combine the mentioned aspects in a systematic way, trying to couple with their related issues.
According to CIMO logic, he aim is to develop, considering manufacturing firms (Context), a structured methodology and framework (Intervention) allowing the exploitation of machine learning and strategic tools (Mechanism) to design CE oriented products (Outcome).

3. Gaps and Objectives

As concerns the use of machine learning for solving different de-manufacturing issues, no practical implementations nor clear frameworks illustrating the path to be followed are present. What is missing is a proper **stage setting**, i.e., a preliminary step to be performed in order to allow a systematic implementation of enabling technologies for solving specific operational and tactical needs in the adoption of Circular Economy strategies. To make and example, it is impossible to have an algorithm able to perform hard disassembly tasks if the product was not designed for enabling this kind of activity.
This work poses itself at strategic level, providing a framework for supporting the design of products for Circular Economy purposes, i.e., for enabling future ML implementations at operational level through the design of the entire lifecycle of the product.
This is carried out considering the design phase as a multi-stage process, which requires many inputs to be considered and a high level of integration and collaboration between companies.
Until now, research and experiments on the introduction of AI in designing products are built considering the design phase as a simple, single stage one. This do not take into account the always increasing complexity of products' structure and the unbreakable relation linking product to process and system.
This work combines

- Structured and multi-stage design approach in a co-evolutionary perspective
- Lifecycle oriented design
- Exploitation of machine learning and generative design

For enabling the future use of machine learning for de-manufacturing processes, and in general for facilitating the introduction of CE strategies.

4. Framework

Built considering product design, process, and system together, the developed framework is illustrated in Figure 1.

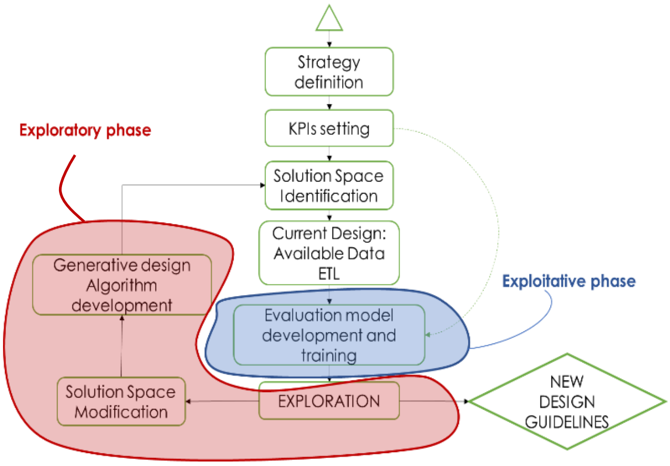

Figure 1- Framework of reference

The framework starts with the definition of the company strategy and the identification of the main business areas which will be impacted by the new pursued product design. This phase deals with the decisions about the supply chain organization, the reverse chain management, the specific circular economy approach that is willing to adopt, the key partners and activities, and with the possible re-thinking of the revenue stream and the way relationships with customers are built. In other words, the required level of integration and synergies between product, process and system leads to the redefinition of the entire business model. The second phase is a proper setting of measures for evaluating and assessing the performances of the company at every point in time, during the undertaken path. KPIs must cover

- system performances,
- processes efficiency and effectiveness,
- product design compliance to requirements

under the **manufacturing** and **remanufacturing** perspectives. This means that the set of measures must be chosen in such a way to guarantee the right assessment of circular economy related performances together with traditional economical and operational indicators. These last indicators are for example ROE, EBITDA, lead time, time to market ecc., while the circular economy related performances must be assessed with an integrated, holistic and scalable set of measures considering product, process and system together.
After these preliminary phases, the framework continues with the definition of the current space of solutions, intended as the set of features and requirements that the product must satisfy. This space of feasible solutions can be divided into three main areas:

- **Product Definition**, i.e., features of the product responding to specific customers' needs.
- **Design Variables**, i.e., technical, engineering specifications of the product.
- **Constraints** represented by Circular Economy requirements.

Once drafted, the list of features and attributes defining the solution space must be structured and transformed in a ordinate and readable set of data. The big effort in this phase lies in the translation of the unstructured information in a set of data which can be collected in an ordered and systematic way, and in the assignment of a relative importance to these data.
The next step is a benchmark between needed data, i.e., those defined in the previous stage, and currently available ones. Due to issues related to data collection, it is common that companies are not provided with the tools for collecting the entire set of data they need for developing the method. In this case, a preliminary iteration of the method can be concluded with the modification of the informative system of the company, with the introduction of new tools for gathering data, with the collaboration with other companies or with the initial modification of the product design, in a way which allows needed data collection. In this sense, the developed method tackles the issues related to the lack of clear guidelines and systematic approaches for data collection, providing a tool for identifying the needed data and consequently gather them. Once fundamental data about the current product design are available, they have to be properly cleaned and pre-processed, following the traditional Data Mining activities, illustrated in Figure 2.

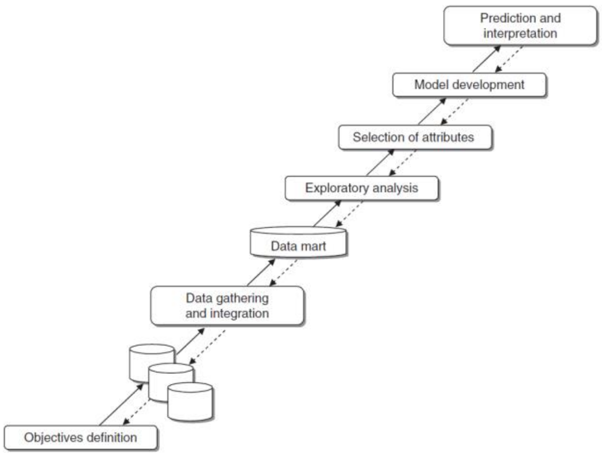

Figure 2- Data mining process

Data present in the dataset (data mart) are split into categorical and numerical attributes, in order to be properly treated in the phase of "exploratory data analysis".
This is done to perform the core part of the method, which consists in the **evaluation** of current design configurations under the defined measures of interest. In this phase, the defined KPIs specifically targeting the product are used for modelling configurations to evaluate them and assess their level of adherence to requirements.

4.1. Evaluation phase

For evaluating existing configurations, the prepared data are used as input to feed regressive algorithms able to learn the existing relations between product characteristics and specifications and the related KPI. **n** different algorithms have to be trained, being **n** the number of defined measures used to assess the goodness of the configuration (i.e., the KPIs). The stage of attributes selection will be different for the trained algorithms since features are selected basing on their relevance and impact on the target variable. Changing the target variable, which is the specific KPI, different attributes will be considered relevant and will be selected. In this direction, the development of these algorithms also acts as a validation of the choice of data. The outputs of the training and development on the n algorithms will be **n** different models which describe the same configurations under different perspectives. In this way, future configurations can be easily evaluated through the trained algorithms and evidence of their ability to satisfy circular needs and customer requirements will be given. The nature of machine learning approach requires that the best algorithm, i.e., the one that performs better in assigning the right value of the KPI to each observation while guaranteeing the right level of generalization, is not known a priori. A grid search must be performed for testing different algorithms in a "try and error" perspective. Different algorithms are evaluated basing on defined measures which are typically:

- MAE, which is the mean average error
- MSE, which is the mean squared error
- RMSE, which stands for root mean squared error
- R squared.

In case of very few data available, clustering can be used for grouping different configurations basing on the degree of their similarity and allowing further analyses to be performed at single cluster level.
The case of new product design requires different approaches to be followed. In this situation, no available configurations are present in the market, and the only input is given by the upstream stage output, i.e., solutions provided by the Generative Design Algorithm. In this case, instead of using Black box machine learning algorithms, the best solution could be that of creating ad-hoc white box models, exploiting the knowledge of the physics behind the object design. White-box models, indeed, are based on known physical laws which are able to model the drafted product configuration (general representation) and link it to specific measures of interest. This process requires big efforts in the study of existing relations between variables, but it allows to extend the method to products for which old configurations are not available, or to companies which have a deep knowledge on the physics behind a product and prefer to apply them for evaluating solutions.
Even in case of already existing products, each company can decide whether to develop white or black box models, or even to go for a double evaluation, trying to develop both approaches for improving the robustness of results.
At the end of this stage, the output is a set of models describing the behavior of different configurations basing on n relevant metrics.
This is fundamental for any kind of design process since it provides a clear and structured approach

for evaluating feasible or already existing configurations.

4.2. Exploratory phase

Exploration of results includes the merging of the different evaluations in a unique result, allowing to choose the best configuration or configurations.
This can be done with the creation of a multi-objective function, which comprehends all the measures of interest and synthesizes them in a single objective.
After that, decision must be taken on whether to be satisfied with existing solutions or to generate new product configurations, after a proper adjustment of the solution space.
In the first case, design guidelines are set, and a standard can be introduced, corresponding to product specifications related to the best configuration.
In the other case, the new space of feasible solutions can be fed into a generative design algorithm.

4.3. Generative Design Phase

Generative design is an extensive explorative design process which consists in giving design goals as input to the generative design process, along with parameters such as performance, spatial requirements, materials, manufacturing methods, cost constraints etc. Unlike optimization, the system explores all possible permutations of a solution by quickly generating many design alternatives. The system learns through testing and receiving feedback on the various iterations of a solution, and applies updates based on that feedback to the next iteration, until the design satisfies the objectives required.
Depending on the effort the company wants to put in preliminary phases and in training the algorithm, different approaches can be selected, which require different inputs and which consequently lead to diverse levels of quality of results. Lowest quality is gained with random sampling approach, which typically relies on pseudo-random number generators. In this case, bigger effort should be put in the next phase of evaluation and exploration of results. As shown in Figure 1, indeed, after generative design algorithm implementation, the process should be re-iterated for testing and evaluating the generated solutions.

5. Lithium-ion Batteries

The described method is applied to Lithium-ion batteries for Electric vehicles. The design complexity of this product and its logistic system, its complicated end-of-life management, and its increasing importance due to the growth of electric mobility market leads to the need to define a systematic way to tackle all these issues.
After a careful selection of needed data defining the space of solutions, carried out through an in-depth study on the functioning and architecture of battery packs, the phase of evaluation of current configuration has been performed. This was done considering a peculiar measure of interest when dealing with circular economy purposes: the **easiness of disassembly** of the product.
Regressive algorithms were trained, feeding them with the relevant data selected and collected starting from existing electric vehicles models. The algorithm which performed best in learning and predicting the relationships between independent input variables (i.e., attributes corresponding to the product definition, the design variables and the CE constraints) and the easiness of disassembly was a Lasso regression algorithm, whose equation is reported in Equation 1. Performances of the algorithm and its hyperparameter are reported in Table 1.

$$\min_{\underline{w}} RR\,(\underline{w}\ , D) = \min_{\underline{w}} \lambda\,|w| + \sum_{i=1}^{m}(yi - \underline{w}'xi)^2$$

Equation 1 - Lasso regression

Best score: Lasso Regressor	*Negative Mean Squared Error = -0.550333*	
Best hyperparameters	Generalization term λ= 0.01	Normalize = False
PERFORMANCES	**Train set**	**Test set**
Mean Absolute Error	0.361	0.452
Mean Squared Error	0.215	0.333
Root Mean Squared Error	0.463	0.577
R squared	0.763	0.673

Table 1 - Selected algorithm Performances

This was part of the evaluation phase, done for a single KPI (easiness of disassembly). The method can be fully performed, with the training of the other regressive algorithms able to evaluate configurations according to all the measures of interest identified. In the work, 10 KPIs are proposed, which cover all the aspects related to customers satisfaction (both B2B and B2C) and Circular Economy needs.
Next steps of the framework application would lead to the exploration of results and se consequent decision on whether to be satisfied with an existing solution or to generate new design alternatives, as shown in Figure 3.

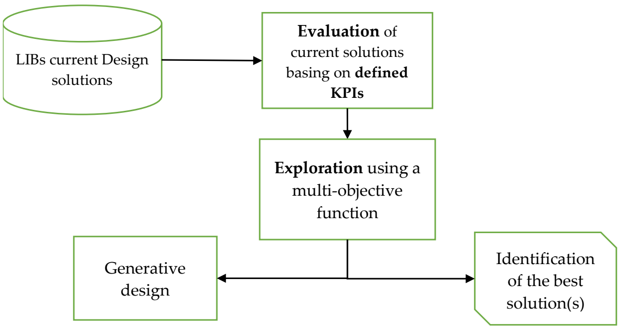

Figure 3 - Framework application to LIB packs

6. Conclusions

The developed framework poses the attention on three important aspects: the fact that the phase of product design is complex and multi-stage and must be tackled accordingly, in a systematic way; important improvements should be addressed in a collaborative way, with the co-operation between all the companies involved; the introduction of enabling technologies like machine learning and generative design must be intended as a tool to support important decisions, always taken by humans.
Compared to related research in generative design and in the use of AI for designing products, this work contributes by including all the aspects related to the business management and to the exploitation of synergies for manufacturers, by considering Circular Economy requirements as fundamental constraints when designing a product in order to simultaneously design its lifecycle, and by creating a more generic framework that shows the technical and strategical workflow of the generative design system.
It also contributes by further exploring the effects of the framework adoption on potential future iterations, explaining the benefits of a closed loop methodology aimed at continuously improve results.
Finally, the field of generative design and its application in the lithium-ion batteries for EV context shows promises and has the potential to be a part of a future designer's toolkit. The main findings in this direction regard the

- validation of the relevant set of variables for describing the easiness of disassembly behavior (mix of categorical and numerical variables), and
- the values assumed by these variables which characterize a configuration that is easy to disassemble. Furthermore, the
- identification of a precise model for describing such behavior, which can be easily replicated for other behaviors.

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