



HAL
open science

Ecodesign approach for complex systems – Electric Vehicle case study

Nicolas Tchertchian, Thomas Richard de la Tour, Dominique Millet, Raphaël Chenouard

► **To cite this version:**

Nicolas Tchertchian, Thomas Richard de la Tour, Dominique Millet, Raphaël Chenouard. Ecodesign approach for complex systems – Electric Vehicle case study. *Procedia CIRP*, 2024, 122, pp.1006-1011. 10.1016/j.procir.2024.02.035 . hal-04595619

HAL Id: hal-04595619

<https://hal.science/hal-04595619>

Submitted on 31 May 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

31st CIRP Conference on Life Cycle Engineering (LCE 2024)

Ecodesign approach for complex systems – Electric Vehicle case study

Nicolas Tchertchian^{a,*}, Thomas Richard de la Tour^b, Dominique Millet^a, Raphaël Chenouard^b

^aCOSMER, Université de Toulon, Toulon, France

^bLS2N, Ecole Centrale de Nantes, Nantes, France

* Corresponding author. E-mail address: Nicolas.tchertchian@univ-tln.fr

Abstract

The reduction of environmental impacts from the early stages of product and system design is a major challenge. Thus, traditional ecodesign methods are not appropriate because they reason by fixing the functional definition of products/systems and address the complexity of these new systems in a simplistic way, which leads to a marginal reduction of impacts. Moreover, these methods do not consider the attractiveness for users, leading to an optimization oriented towards functional reduction. In this paper, a comprehensive ecodesign approach is presented suggesting a paradigm shift, which involves a hybrid ecodesign approach based on constraint modeling of systems based on the constraint satisfaction problem formalism (CSP) with more traditional environmental assessment methods to decide which design choices to make. This approach was applied to generate and characterize product and life cycle architectures of a serial hybrid vehicle powertrain focusing on the use and end-of-life phase.

© 2024 The Authors. Published by Elsevier B.V.

This is an open access article under the CC BY-NC-ND license (<https://creativecommons.org/licenses/by-nc-nd/4.0>)

Peer-review under responsibility of the scientific committee of the 31st CIRP Conference on Life Cycle Engineering (LCE 2024)

Keywords: Ecodesign ; Early design stage ; Product Architecture ; Lifecycle Architecture ; CSP

1. Introduction

Our society is increasingly concerned about environmental issues. The accelerated pace of product renewal is causing accelerated exploitation of raw materials (Mater.) and energy. Today, with an annual consumption of raw materials of about 60 billion tons, the world's population consumes about 50% more natural resources than 30 years ago. In OECD countries, the household waste stream increased by 40% in volume between 1980 and 1997. Designing environmentally friendly products has become an essential requirement. Numerous ecodesign methods have been developed, but they do not allow us to explore all possible architectural solutions within an acceptable time frame. For example, many approaches have been developed in the literature to help the designer identify and select the right materials for predefined concepts [1], [2], [3], [4]; the drawback of these approaches is that they do not consider the multiple interconnections with the product on

which it depends [5]. Research [6] has highlighted the importance of an iterative and flexible approach to design, which could be extended to the context of ecodesign. The integration of emerging technologies such as artificial intelligence into the eco-design process is also a subject addressed in the literature [7]. Researchers, particularly in the field of computer-aided design, have examined how machine learning algorithms can help to optimise design by taking environmental criteria into account. The existing literature demonstrates a widespread use of optimization methods aimed at generating architectures that offer the best trade-offs among various performance criteria. Mathematical models are used in areas such as pre-design [8], solving sizing problems [9], [10], optimization [11], [12] product platform configuration [17]. The effectiveness of CSP approaches is also proven for modeling the product usage phase [14]. There are limits to these methods: models used are rough, and mathematical optima are only valid if models are accurate; The number of performance

criteria can be large in ecodesign problems, and it becomes more complex to prioritize these criteria or identify the optima; And the results of multi-objective optimization provide only a limited overview of achievable solutions.

Moreover, they reason according to a principle of fixed functional unit, which greatly disable the optimization of the sustainability of a complex system. Improving the attractiveness of a product can be done by taking better account of customer requirements. This must allow designers to design a product that best meets stakeholders' expectations and therefore likely to meet a large success on its market. Among the most used techniques for this purpose are QFD [15], QFD for Environment [16], the Environmentally Conscious QFD [17].

The structure of this document is as follows:

In section 2, a brief overview of the global ecodesign approach is given and applied to the automotive industry. In section 3, details on how to generate a Product and Life Cycle Architecture are provided. And finally in section 4 an example of product and life cycle architecture generation on the powertrain subsystem of a hybrid vehicle is presented.

2. Presentation of a global approach to ecodesign of sustainable systems

A SADT (Structured Analysis and Design Technique) diagram illustrates the global approach of the method.

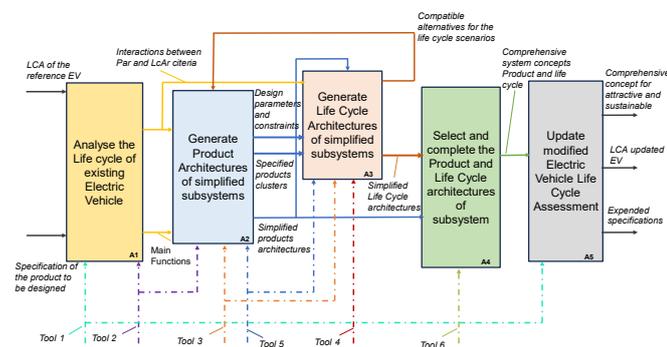


Figure 1: Framework of Method to ecodesign sustainable and attractive electric vehicle

The objective of this design method is to help stakeholders design a high-performance, attractive and sustainable system, starting from the preliminary design phase (Pahl et al., 2007) [18]. The deliverable of this method is to generate preliminary system architectures, combining a Product Architecture (PAr) and a Life Cycle Architecture (LcAr), in terms of environmental, economic and user attractiveness. The method focuses on the early stages of design process, as it corresponds to the stage where the cost/benefit ratio is the most important, especially for reducing the final environmental impact.

A design method is a particular 'object' in the sense that the functions it must satisfy are not obvious, they are often more abstract than practical. Our belief is that a method intended for design, in a general way, is an object that must satisfy two categories of requirements (technical and social).

- The first step of the method (A1) is to analyse the system. More specifically, it consists in extracting the LCA of the subsystem from an available LCA of a close enough existing complete system; defining the specifications of the subsystem, specifying the performance criteria, the level of functions and the attractiveness of the functions for the user via a score from 1 to 10; and imagining promising concepts, based on technological modules (Mod) (modules are a group of components that perform the same functions) from databases specific to the automotive industry. This step is crucial to ensure innovation, especially in environmental terms.

- The second step of the method (A2) and (A3) consists in exploring in a disjointed/decoupled way Product architectures and Life Cycle architectures. This step allows us to consider all the possible solutions by exploring the entire design space, focusing on the most impactful components. A2 and A3 will be detailed in the following paragraph.

- The fourth step (A4) consists in converging and rationalizing the PAr and LcAr into a complete concept of a coherent and environmentally (and economically) optimized system integrating all components (impacting and non-impacting). At the end of step A4 an enriched specification and complete concepts of attractive and sustainable systems are generated.

- The final step (A5) allows to update the LCA of the new system (current "amputated" system + eco-designed subsystem). This provides the environmental performance of the complete vehicle at the end of the ecodesign process.

In this article, the Product and Life Cycle Architecture generation phases are presented in more detail. To help the designer to apply the method, six tools have been developed:

- Tool 1: a life cycle analysis tool.
- Tool 2: a tool for formulating attractiveness objectives.
- Tool 3: a tool for selecting impact modules.
- Tool 4: a tool for identifying life cycle assets.
- Tool 5: a CSP modeling tool.
- Tool 6: a tool for analyzing and visualizing results.

These tools appear as support in the SADT diagram of the approach (Figure 1) but have not been detailed in this article.

3. Exploration and Generation of Product Architecture and Lifecycle Architecture

3.1. Constraint-based problem modeling (CSP)

In this paper, a reversal reasoning in ecodesign process is proposed, by rigorously aggregating from the start all the constraints associated with environmental impacts to specify the design problem in a systemic way and to be able to launch a systematic and automated exploration process for solutions that simultaneously satisfies all the objectives and constraints at once. Technically, this new eco-design approach is based on mathematical modelling of the problem by constraints (CSP) and its solving by a design space exploration algorithm or an

optimization algorithm. This part of the method includes 2 steps:

A) A formulation by a set of variables $X = \{x_1, x_2, \dots, x_n\}$, each in a domain $D = \{d_1, d_2, \dots, d_n\}$ (discrete or continuous), while satisfying a set of constraints $C = \{c_1, c_2, \dots, c_k\}$. A solution of a CSP is the instantiation of each of the variables of X in the domain D while satisfying the set C of constraints of the problem. Design problems are often CSPs with mixed variables and nonlinear constraints.

B) A partial exploration algorithm [19] [20] then generates a few representative solutions, i.e., well distributed in the feasible space. The hybridization of a CSP approach and ecodesign is original.

Partial exploration is used to deal with the growing number of design objectives and to support interaction between the designer and the solution space.

This article details the A2 and A3 phases of the above proposed method.

3.2. Product Architecture generation

Figure 2 illustrates the product architecture generation process. To simplify the exploration in the early design of the system, designers need to identify the most impacting modules according to environmental criteria (global warming potential, Eutrophication, Abiotic depletion, acidification and Cumulative Energy Demand), production cost and influence on the functional unit. The three impacting modules are modeled by the designer (design parameters, constraints and constants), other modules are considered fixed in the architecture, in accordance with similar existing systems. To maximize the attractiveness of the system, the influence of the design variables on the functional performances are checked, which are attractive for the user, and cost function to be optimized is defined to focus the research on the most attractive architectures (the detail of the calculation of these objectives is not treated in this article). Designers should describe the system in the CSP formalism (design variables, constraints, table of available components and already fixed variables/components as constants). A solver is used to generate the feasible physical architectures of the system to design. These solutions correspond to an instantiation of the design variables. The last step of the process consists in grouping the solutions into Product Architecture families according to some relevant criteria. In practice, all the solutions will be represented in a Parallel Coordinates Plot type graph (PCP) highlighting some clusters of architectures that are quite close on some criteria.

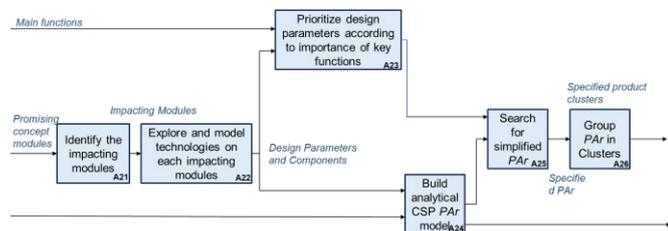


Figure 2: Product Architecture (PAr) generation process

3.3. Life cycle Architecture generation

Figure 3 illustrates the process of generating life cycle architectures. To simplify the exploration, designers need to identify the improvement opportunities on the life cycle stages of all the modules of the promising concept. A tool (not presented in this paper) allows the designers to compare the reference life cycle scenario of the module with an improved scenario on environmental criteria (global warming potential, Eutrophication, Abiotic depletion, acidification, cumulative energy demand) and costs. The designer models the life cycle phases identified as potentially generating environmental improvements and writes it in the CSP formalism.

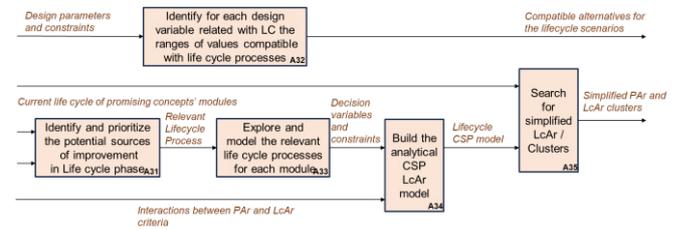


Figure 3: Lifecycle Architecture (LcAr) generation process

3.4. Research process

The solution selection process, described figure 4, begins with the generation of numerous product architectures based on the product model. A solver, IBEX [21], and search algorithms are used to explore the diversity of these architectures. Component properties, such as mass (M.), material and impact, are specified for each solution through the propagation of product constraints.

A Python script has been developed to visualise this exploration and rank the solutions according to performance criteria (environmental and economic). The most promising solutions are selected. In the second stage, the lifecycle model is updated using common variables, ensuring compatibility between the product and lifecycle architectures. The properties of the life cycle stage, such as end-of-life destination and consumption in the use phase, are specified for each solution by propagating life cycle constraints. The process is iterative, enabling progressively refine the architectures according to the constraints identified throughout the process.

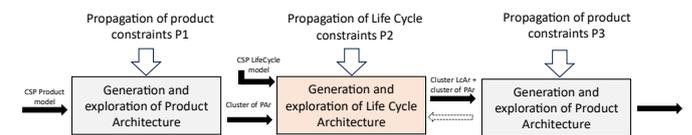


Figure 4: Research process of the Product architectures and Life Cycle architectures

4. Case study: Ecodesign of the powertrain of a hybrid vehicle

4.1. Modeling the powertrain

To meet the regulations imposed on greenhouse gas emissions,

car manufacturers have taken the path of electrifying the vehicle drive train (Hybridization or total electrification). In the case of hybrid systems, the power (P.) consumption of the powertrain depends largely on the efficiency of the energy converter. Today's hybrid vehicles use the internal combustion engine to supply energy to batteries and an electric motor. There are different Gas Turbines architectures (Figure 5) [22], these configurations (Config.) include a single Gas Turbine (GT), Regenerative Gas Turbine (RGT), Regenerative Gas Turbine with Intercooler (IRGT) and Regenerative Gas Turbine with Intercooler and Reheat (IRReGT) which have different efficiency and power to weight ratio.

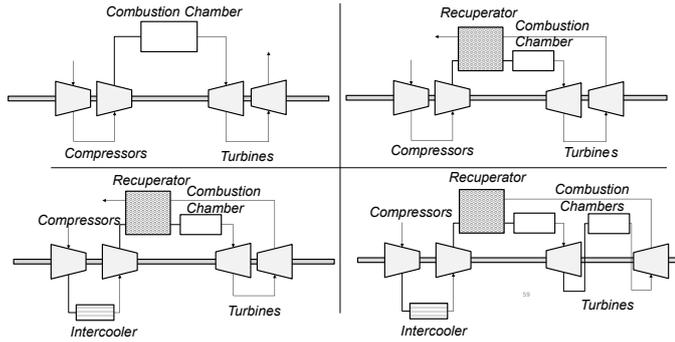


Figure 5: Gas Turbine configuration: a) GT; b) RGT; c) IRGT; d) IRReGT.

The system consists of a gas turbine, generator, inverter and a battery pack, the elements of the turbogenerator are a turbine, a compressor, a combustion chamber, possibly radiators (the recuperator heats the air, and the intercooler cools the air to increase efficiencies), and depending on the configuration an exhaust, thermal and acoustic insulators and a cooling.

A semi-empirical model is developed from the experimental data [22]:

- Power-to-weight ratio as a function of air mass flow for different rotational speeds and for different turbochargers studied.
- Mass of the turbocharger as a function of the power and the combustion temperature
- Mass of the radiators as a function of the power and the combustion temperature

The modeling of this system requires the definition of the following physical equations:

The electric motor is designed to accelerate from 0 to 100 km/h in 10 seconds. The maximum power of the Electric Motor is given by equation 1.

$$P_{EM} = \frac{M_v}{2 \cdot t_a} (V_f^2 + V_b^2) + \frac{2}{3} M_v g f_r V_f + \frac{1}{5} \rho C_x S V_f^3 \quad (1)$$

The gas turbine is sized taking into consideration the WLTC (Worldwide harmonized Light vehicles Test Cycles) usage cycle, and the average power of each phase of WLTC is calculated using equation 2.

$$P_{GT}(V_i) = \frac{V_i}{\eta_g \cdot \eta_t \cdot \eta_m} (M_v g f_r + \frac{1}{2} \rho C_x S V_i^2) \quad (2)$$

The battery must provide sufficient traction power, with support from the gas turbine in the case of maximum power demand. Therefore, the maximum power of the battery is sized using the equation 3.

$$P_b \geq \frac{P_{EM}}{\eta_{EM}} - P_{GT} \eta_{GT} \quad (3)$$

The battery energy consumption depends on the power of the electric motor, auxiliaries, electric heating, supplemented with Gas Turbine when activated (equation 4).

$$(P_{EM} + P_{aux} + P_{Hot\ thermal}) * T = P_{GT} * T + (SOC_{Max} - SOC_{Min}) * C_b \quad (4)$$

The vehicle's fuel consumption is calculated using the equation 5.

$$\dot{m}_{Fuel}(t) = \frac{P_{GT}(t)}{\eta_{GT} H_v}$$

4.2. Exploration phase of the product architectures

The objective of the application is to characterize the architecture of the TG (1-GT, 2-RGT, 3-IRGT, 4-IRReGT), the different components (material, mass and impact), the power of the system and the quantity of battery to be added. For the sake of readability of the graph (Figure 6), materials of the modules are represented. In our application, alternatives for each module of the TG are discrete variables, two materials for turbines and compressors (1-Steel, 2-Ferro-Nickel), two materials for recuperator and intercooler (1-Steel, 2-Aluminium), three types of combustion chamber depending on combustion temperatures (1- Steel, 2- Ferro-Nickel, 3- Ferro-Nickel + Ceramic) and seven types of chemistry for the battery cells (1-NMC₁₁₁, 2-NMC₈₁₁, 3-NMC₆₂₂, 4-NMC₅₃₂, 5-NCA, 6-LFP, 7-LMO).

Table 1. Variables and constants of the system.

constant	Value	unit	Description
M _v	1210	kg	Vehicle mass
S	2.17	m ²	Frontal area
C _x	0.29	-	Drag coefficient
f _r	0.0106	-	Wheel friction
ρ	1.205	Kg/m ³	Air density
g	9.81	m/s ²	gravity
V _f	100	Km/h	Maximal Acceleration
V _b	50	Km/h	Motor base speed
t _a	10	s	Acceleration 0-100kmh
P _{aux}	750	W	Auxiliaries' consumption
H _v	42.5	MJ/kg	Fuel heating value
η _g	95	%	Generator efficiency
η _m	93	%	Motor efficiency
η _t	97	%	Transmission efficiency
Variables	Unit	Description	

P_{EM}	kW	Motor maximum Power
P_{GT}	kW	GT system power
η_{GT}	%	GT efficiency
P_b	kWh	Battery maximum Power
C_b	kWh	Battery capacity

The IBEX library combined with dedicated design search algorithms are used to generate a variety of turbine generator architectures in the feasible design space. These solutions are represented as a PCP graph. This representation allows to identify clusters, visually, on 3 or 4 discriminating parameters (TG configurations and materials for components).

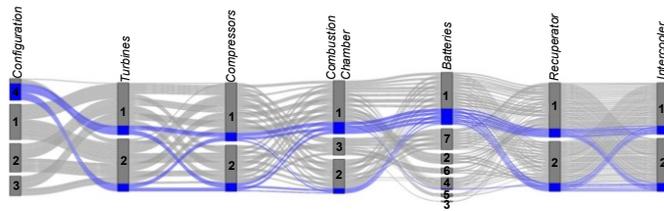


Figure 6: Parallel Coordinates Plot of Product Architecture (PAR)

Then, a post-process is applied on the set of computed solutions to collect the solutions per cluster according to the discriminating parameters. Finally, the range or interval of relevant values for design variables are re-evaluated inside each cluster. On Figure 6, four clusters are identified following the four possible product architecture topologies since they imply different components as presented earlier. From a Python script, the solutions are prioritised according to the global warming indicator for the raw materials and manufacturing phases. The best solutions are highlighted in blue in the figure 6. As the propagations progress, the product architectures and then the lifecycle architectures are refined at the same time as the intervals are reduced. The impact of the Product architectures on the global warming indicator varies between 1050 and 2300 kg. CO₂-eq for a power range between 19 kW and 24 kW. The identified clusters are then used to explore the life cycle architectures. The results are collected in table 1 as propagation 1 (P1).

4.3. Architecture exploration phase Life cycle

The analysis of the life cycle potential in the methodology shows a strong potential for improvement in the use and end-of-life phases.

At the end-of-life, the design variables are the end-of-life destinations of the modules in percentage: Incineration (Inc.), Landfill (Lan.), Recycling (Rec.) and Reuse (Figure 7). The model has been simplified because it requires many variables. For better readability of the PCP graph, only end-of-life scenarios of combustor and inverter are represented. The impact of the end-of-life of the analysed cluster on the global warming potential indicator varies between 70 and 90 kg. CO₂ eq. A noteworthy result is the presence of a large cluster for the compressor end-of-life configuration: (Lan., Inc., Rec., Reuse) = (0, 50, 50, 0). For the other elements, further iterations are needed to reduce the diversity of end-of-life architectures. The

results are collected in table 3 as propagation 2 (P2).

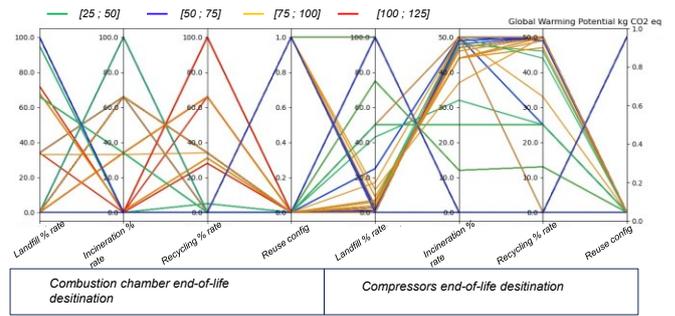


Figure 7: Parallel Coordinates Plot of Life Cycle Architecture (LcAr)

In our study on the use phase, WLTC speeds are now variables to support functional negotiation of vehicle performance. In practice, this translates into the definition of an average speed range on each profile of the WLTC cycle (Table 2). For example, on profile 1 (slow cycle) the average speed is 18.9 km/h, on this profile the vehicle is in electric mode. In the CSP model, the speed of cycle 1 varies between 19 km/h and 21.6 km/h. The objective is to identify the specification of powertrain for the most suitable speed for each WLTC profile. The PCP (Figure 8) illustrates the different possible scenarios and the associated fuel consumption in L/100 km. A slight reduction in the target speed of the 4 phases of the WLTP cycle allows for a reduction in the amount of battery capacity (or an increase in autonomy range) and a reduction in fuel consumption in the thermal phase. The solution selection process shown in Figure 4 is applied and the preliminary results are shown in Table 3 as propagation 2 (P2).

Table 2. WLTC specifications.

Cycle WLTC	Speed (km/h)	Duration (s)	Distance (km)
Low speed	18.9	589	3.1
Medium	39.5	4.33	4.7
High	56.6	455	7.1
Extra High	92	323	8.2

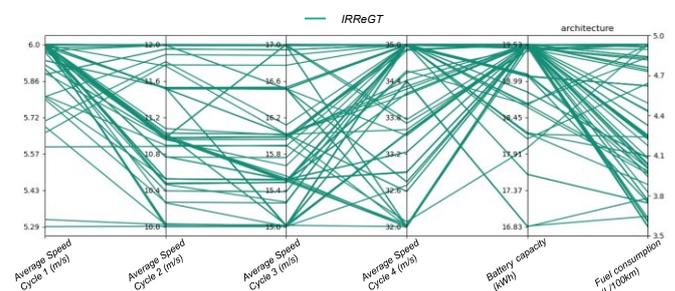


Figure 8: functional negotiation on WLTC average speed

An initial propagation of constraints is used to reduce the ranges of design parameters (design param.) in the product model. The lifecycle model is then updated with the new range of design parameters. A third propagation is used to reduce the design parameters of the life cycle model. Finally, a last propagation is used to reduce the design variables of the product model again (P3) in table 3. This process of coupled

generation between the product architecture and the lifecycle architecture ensures that the product architectures generated are compatible with the lifecycle architectures. This operation can be carried out several times. This means that the solution selection process is iterative, enabling the product and lifecycle architectures to be progressively refined according to the constraints and variables identified throughout the process.

Table 3. Results.

Mod.	Mater.	Design Param.	P1		P2		P3	
			min	max	min	max	min	max
Turbine	steel	M. (kg)	6.6	32.8	6.7	7.5	6.1	7.5
compressor	steel	M. (kg)	2.8	14.1	2.8	3.4	2.8	3.3
Recuperator	steel	M. (kg)	19.9	39.9	25.1	39.8	25.4	26.4
Intercooler	steel	M. (kg)	2.1	2.9	2.5	2.9	2.1	2.9
Battery	NMC ₁₁₁	M. (kg)	45.5	77.6	53.2	62.3	55.5	61.0
		C _b (kWh)	10.1	20.1			16.0	19.6
Combustion Chamber	FeNi	M. kg	3.2	24.1	16.4	16.8	16.4	16.8
		Inc. %			0	11		
		Lan. %			29.5	29.5		
		Rec.%			55	60		
Motor		P. (kW)	75.8	90.3			75.8	80.5
Turbogenerator		P. (kW)	19.1	24.1			20.8	22.4
		Config.	4	4	4	4	4	4
Global Warming Potential impacts GWP (x1000 kgCO ₂ eq.)								
Raw materials		GWP	1.04	2.31			1.28	1.35
Use phase		GWP	6.96	8.86			8.14	8.80
End of life		GWP			0.07	0.08		

Conclusion

This work proposes to apply a methodology to ecodesign (Electric) Vehicles in the preliminary design phase. The CSP modeling allows designers to explore the feasible product architectures, but also the corresponding life cycles. Users, designers and ecodesign experts, must be able to quickly modify constraints or variable domains and observe the evolution of the solution space before any optimization consideration. The partial exploration paradigm also responds to the increasing number of early-stage design criteria in the environmental domain, which is faced with more and more standards to meet. A representative partial set of solutions provides a picture of the feasible design space and allows different designs to be considered for further study.

To conclude, the method proposed and implemented on a case has highlighted 3 major advantages: A method that structures the acquisition and construction of knowledge; a method that lets the designer explore the design space effectively while considering the performance criteria used to assess the relevance of a solution and considering all categories of environmental impact (CO₂ footprint, depletion of resources, human toxicity, eutrophication, etc.). However, the implementation of functional negotiation to produce an attractive product that fully meets the stakeholders' expectations has yet to be achieved and successfully tested on

industrial product.

References

[1] Mayyas, A. T.; Qattawi, A.; Mayyas, A. R.; Omar, M. A. (2012): Life cycle assessment-based selection for a sustainable lightweight body-in-white design, *Energy*, Vol. 39, No. 1, pp. 412–425

[2] Mayyas, A.; Omar, M. A.; Hayajneh, M. T. (2016): Eco-material selection using fuzzy TOPSIS method, *International Journal of Sustainable Engineering*. Vol. 9, No. 5, pp. 292-304.

[3] Zhou, C. C.; Yin, G. F.; Hu, X. B. (2009): Multi objective optimization of material selection for sustainable products: artificial neural networks and genetic algorithm approach. *Materials and Design*, Vol. 30, pp. 1209–1215.

[4] Reddy, A. S.; Kumar, P. R.; Raj, P. A. (2019): Preference based multi-criteria framework for developing a Sustainable Material Performance Index (SMPI), *International Journal of Sustainable Engineering*

[5] Serafini, M., Russo, D. & Rizzi, C. (2015): Multi Criteria Material Selection for Eco-design, *Computer-Aided Design and Applications*, Vol. 12 No. 5, pp. 526-536.

[6] Blessing, L. T. M.; & Chakrabarti, A. (2009): *DRM, a Design Research Methodology*. Springer-Verlag, London.

[7] Saidani, M.; Kim, H.; Yannou, B. (2021): Can Machine Learning Tools Support the Identification of Sustainable Design Leads From Product Reviews? Opportunities and Challenges. In: *Proceedings of the ASME 2021 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*.

[8] O'Sullivan, B. (2002): Interactive constraint-aided conceptual design. *AI EDAM*, Vol. 16, No. 4, pp. 303-328.

[9] Yvars, P. A. (2010): A Constraint-Based Approach to the Composition Relation Management of a Product Class in Design. *Journal of Computing and Information Science in Engineering*, Vol. 10, No. 3.

[10] Chenouard, R.; Granvilliers, L.; Sébastien, P. (2009): Search Heuristics for Constraints-Aided Design. *AI EDAM*, Vol. 23, No. 2, pp. 175-195.

[11] Hao F.; Merlet J. P. (2005): Multi-criteria optimal design of parallel manipulators based on interval analysis. *Mechanism and Machine Theory*. Vol. 40, No. 2, pp. 157-171.

[12] Mayyas, A.; Qattawi, A.; Omar, M.; Shan, D. (2012): Design for sustainability in automotive industry: A comprehensive review, *Renewable and Sustainable Energy Reviews*, Vol. 16, No. 4, pp. 1845–1862.

[13] Xie, H.; Henderson, P.; Kernahan, M. (2005): Modelling and solving engineering product configuration problems by constraint satisfaction. *706 International Journal of Production Research*. Vol. 43, No. 20, pp. 4455-4469.

[14] Yannou, B.; Wang, J.; Yvars, P. A. (2010): Computation of the Usage Contexts Coverage of a Jigsaw With CSP Techniques, In: *Proceedings of the ASME 2010 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, pp. 369–378.

[15] Akao, Y. (2004): Quality function deployment.

[16] Masui, K.; Sakao, T.; Inaba, A. (2001): Quality function deployment for environment: QFDE (1st report)-a methodology in early stage of DfE, in: *Proceedings Second International Symposium on Environmentally Conscious Design and Inverse Manufacturing*. In: *Proceedings of the 2nd International Symposium on Environmentally Conscious Design and Inverse Manufacturing*, pp. 852–857.

[17] Francis, F. (2009): Environmentally conscious quality function deployment - A new approach for green manufacturing. In : the 2009 International Conference on Advances in Computational Tools for Engineering Applications, pp. 340–343.

[18] Pahl, G.; Beitz, W.; Feldhusen, J.; Grote, K. H. (2007): *Engineering Design, A Systematic Approach*.

[19] de Latour, T.; Chenouard, R.; Granvilliers, L. (2021) : Stratégies de résolution anytime de problèmes de satisfaction de contraintes numériques. Presented at the JFPC, p. 10.

[20] Chenouard, R.; Goldsztejn, A.; Jermann, C. (2009): Search Strategies for an Anytime Usage of the Branch and Prune Algorithm, in: *International Joint Conference on Artificial Intelligence*. United States, pp. 468–473

[21] <http://www.ibex-lib.org/>

[22] Bou Nader, W. (2019): Methodology for the selection and optimization of energy converters for automotive powertrain applications. PhD thesis. PaisTech