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Case-Based Reasoning in Achieving Sustainability Targets of New Products

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Abstract: Improving product sustainability is becoming an increasingly significant challenge for modern enterprises. A growing number of manufacturers are interested in enhancing product sustainability throughout the product life cycle. This study is concerned with using case-based reasoning to identify ways of improving product sustainability and select variables for model specification. Parametric models are applied to search for opportunities to improve product sustainability. This can be achieved through changes introduced at the product design stage. Simulations are performed using constraint-satisfaction modeling to identify conditions for achieving the sustainability targets of new products. Constraint-satisfaction modeling provides a suitable framework for finding all possible sustainability-enhancing changes (if any) during the new product development process. These changes may support R&D specialists in identifying opportunities to improve the sustainability of new products. We demonstrate the usefulness of the proposed approach with an example in which our method enabled a reduction in the product failure rate and an increase of battery lifespan for a robot vacuum cleaner line. We analyzed several factors affecting two targets of product sustainability: minimizing the product failure rate and maximizing battery lifespan. Our findings indicate that R&D staff size is the biggest factor in reducing the product failure rate, and that battery capacity is the most significant factor in battery lifespan.

Keywords: constraint-satisfaction modeling; eco-design; product sustainability; simulations for sustainability development; sustainability performance

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1. Introduction

In recent years, businesses have been paying increasing attention to product sustainability. This is the result not only of environmental restrictions and legal regulations, but also corporate social responsibility policies and growing environmental awareness among consumers. Sustainable products are advantageous for companies from a business image perspective. Moreover, sustainable products offer financial benefits. For instance, the reduction of material and energy consumption in manufacturing can decrease the total product cost. Therefore, more and more manufacturers are interested in improving the sustainability of their products. Consequently, there is a need to make changes to the design process to incorporate sustainability into new products.

Product design affects the successive stages of a product's life, such as manufacturing, product usage, and its recycling and/or disposal. Therefore, the product design process significantly impacts consumer satisfaction and the environment. Changes incorporated into this process can increase product sustainability and its success. For example, choosing to use higher quality materials to manufacture a new product may reduce its failure rate, thus increasing its reliability and longevity.

The majority of contemporary companies use information systems to support their business processes, including product design and manufacturing. The data related to these processes are registered in company databases, and such data may be further used for business analytics to support decision makers. The design process is supported by computer-aided design (CAD) and computer-aided engineering (CAE) software. Production, sales, and accounting processes can be supported by an enterprise resource planning (ERP) system. Data related to customer complaints, requirements, and responses to advertising campaigns may be stored in a customer relationship management (CRM) system. These databases may be employed not only to register business processes, but also as a data source for deeper insights into the performance of previous product, and as a means of improving the sustainability of a new product. Case-based reasoning (CBR) methodology is a pertinent tool for assessing product sustainability and identifying solutions to the problem of improving product sustainability. Moreover, a simulation approach seems to be a suitable tool of identifying possible changes in product design by which a target level of product sustainability can be achieved.

The goal of this study is to develop an approach to identifying opportunities to increase the sustainability of a new product during the product design stage. The proposed approach consists of an assessment of product sustainability, the identification of solutions to potential sustainability problems, and the identification of possible changes in the new product development process to enable the achievement of sustainability targets. This approach applies CBR methodology and constraint-satisfaction modeling (CSM) to the problem of improving product sustainability. CBR facilitates the selection of variables to be used in parametric models that are then applied to identify relationships and find possible ways to increase product sustainability. The number of all possible solutions is usually vast, which creates a need to reduce processing time. To perform this task, a constraint programming (CP) environment has been proposed. CP is implemented within constraint-satisfaction modeling. The advantage of the proposed approach lies in its ability to identify possible solutions (if any) to problems of product design. The changes to the new-product development process proposed by our system are intended to increase product sustainability and allow companies to achieve sustainability targets. Moreover, defining a problem in CSM terms may be a suitable tool to use in developing a decision-support system.

CSM may be effectively applied to various areas of product development—for instance, in design concept generation [1] or life-cycle cost analysis [2]. Nevertheless, CSM has so far rarely been utilized in the area of increasing product sustainability. CSM is most often applied to supporting sustainable supply chains [3,4]. Improving product sustainability by merging CBR and CSM to identify and introduce improvements during product design has not yet been considered in the literature. This is our motivation for developing an approach that would support research and development (R&D) specialists in obtaining information on feasible changes during the design stage—changes through which sustainability targets for a new product could be achieved. The novelty of this research lies in two areas: (1) the use of CSM to define the problem to be considered, and (2) the employment of CBR methodology to assess product sustainability and find similar cases to which solutions to the current design problem can be applied. The latter is related to the search for opportunities to modify a product's design so as to achieve sustainability targets. Consequently, the proposed approach allows R&D staff members to gain information on permissible changes (if any) in the product design process.

This paper consists of six sections. Section 2 includes a literature review regarding product sustainability, case-based reasoning in sustainable design, and simulations used to achieve product sustainability targets. The proposed approach to assessing product sustainability and achieving sustainability targets for a new product is presented in Section 3. Its applicability is illustrated in Section 4. Finally, Sections 5 and 6 provide a discussion and conclusion, respectively.

2. Literature Review

2.1. Product Sustainability

Sustainability is the concept of achieving a trade-off between environmental cleanliness, social responsibility, and economic success. The environmental, social, and economic pillars of sustainability are often called the "triple bottom line". A contemporary enterprise should seek to reach a compromise between design, manufacturing, and environmental concerns. At present, product sustainability assessments include not only manufacturing processes and product use but also product recycling or disposal as well as possible reuse or remanufacturing.

Preceding a product's life cycle, product design is a process that plays a crucial role in incorporating sustainability into a new product. The design process includes the selection of materials needed for manufacturing, component design and assembly, and methods of product recycling or disposal. Product functionality is the main goal of product design. However, this process should also strive for other objectives, which can include sustainable manufacturing and product sustainability.

Sustainable manufacturing recognizes three issues regarding sustainability: the minimization of the use of energy and naturally limited resources (environmental), producing profitable products (economic), and manufacturing products safe for consumers, employees, and communities (social) [5]. Adopting the sustainability concept requires a manufacturing company to follow a holistic approach, embracing the perspectives of product design, manufacturing processes, supply chain, and multiple life cycles of the product.

Sustainable products are developed by improving the quality of materials, supply chains, and product reliability. The drive to produce sustainable products pushes enterprises toward introducing the concept of sustainable manufacturing. This refers to the use of more sustainable materials or the reduced consumption of scarce resources [6]. Recently, sustainable manufacturing has often been associated with the concept of a circular economy and closed-loop supply chains [7–9].

Eco-design involves designing products according to the triple bottom line, enriching other product features such as functionality, profitability, quality, aesthetics, etc. The primary purpose of eco-design is to reduce negative environmental impacts and resource consumption while improving product value [10]. There are several methods and tools for assessing environmental issues in a new product. One of them is a quantitative tool based on a life-cycle cost analysis that merges environmental and economic aspects. Another tool employs an eco-design checklist that enables a rapid environmental assessment of product design through answers to environmental questions such as: Are hazardous substances avoided in the new product?; Is the consumption of materials minimized?; Is there an easy way to disassemble, reuse, or recycle the product, or are biodegradable materials utilized? A review of methods and tools employed to assess environmental issues in a new product is presented in [11].

Indicators for assessing a sustainable product can be classified into three categories according to the pillars of sustainability: economic, environmental, and social costs. Economic-pillar indicators include material and labor costs (direct costs), potential hidden costs (e.g., product disposal costs), contingent costs (e.g., customer warranty costs), relationship cost (e.g., costs accruing due to loss of goodwill as a result of customer concerns), and external costs (e.g., depletion of resources). Environmental-pillar indicators involve material consumption (including product and packaging mass, the product's useful lifetime, and the amount of hazardous materials used in the product), energy consumption (including energy consumed over the product's life cycle and in the manufacturing process), local impact (e.g., in the context of recyclability), regional impact (e.g., in the context of smog, acidification of rain, or biodiversity) and global impact (e.g., in the context of carbon dioxide emission, or ozone depletion). Social-pillar indicators include issues related to quality of life (including product availability, knowledge or skill improvement), reductions of illness and disease as a result of the product's use, accident and injury reductions, and health- and wellness-related impacts [12].

2.2. Case-Based Reasoning in Eco-Design

The design process is one of the most challenging problem-solving activities in manufacturing companies. It should encompass the complete product life cycle, from prototype testing to product recycling/disposal. There are several approaches to supporting product design. One is case-based reasoning (CBR). It helps find answers to new problems by using knowledge obtained from solutions to past problems. CBR taps into a case base to retrieve solutions to similar problems encountered in the past. A CBR system should adapt the retrieved case or solution(s) to the current problem, then evaluate the adapted case. CBR is an alternative to paradigms related to rule-based and model-based reasoning. It can be seen as an experience-based method that does not generalize knowledge into rules and models [13].

CBR is an approach designed to find solutions to a problem by applying analogical reasoning in which past problems or experiences may provide some assistance in surmounting the current problem. Analogy plays a significant role in understanding and resolving the problem at hand. There are two main tasks in CBR [14]: (1) identifying a relevant past experience and (2) determining what is similar and what has changed. The former involves searching the case base for one or more cases according to predefined features or attributes describing the new problem. For instance, the problem of reducing product weight can be solved by identifying previous products whose weight was reduced within the set parameters. The second task involves adjusting features or attributes of the retrieved case to match it to the new problem. For example, if the weight of a new product should be reduced by about 2% more than the previous product (retrieved case), adjustments should be made to other related attributes (e.g., material density, product size). Other prediction and/or simulation techniques are also available to adjust the past case and solve the new problem. Figure 1 illustrates the application of CBR to solve the new problem.

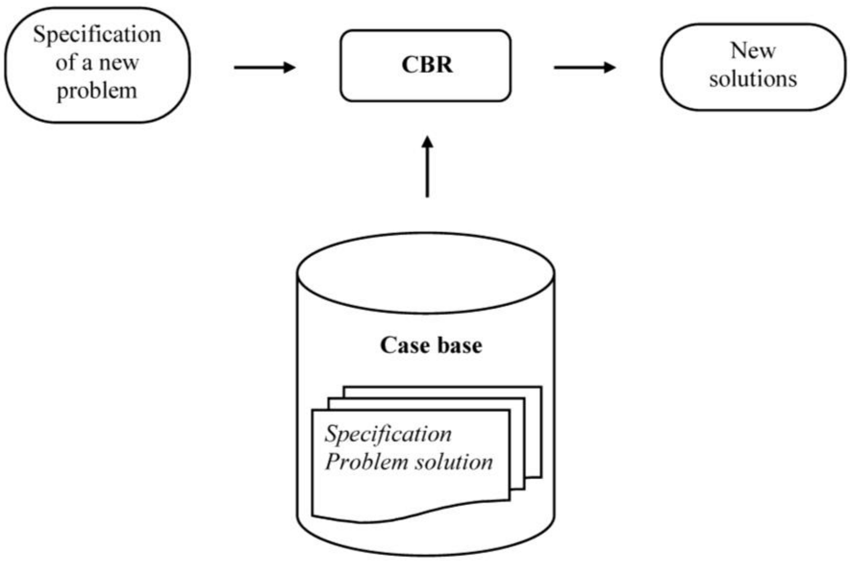

Figure 1. CBR concept.

CBR can support designers by providing previous experiences that are potentially helpful for solving a design problem. CBR seems to be a suitable model of the design process because much of the design knowledge is acquired from specific previous design situations [14]. One of the most important tasks in the development of product design support tools is that of identifying the design knowledge that should be included in dedicated software. The CBR methodology helps designers find previous design situations similar to the new situation without having to convert the design knowledge into rules or models. This solution is usually preferred by designers, resulting in many applications of

CBR to product designs [15–19]. Nevertheless, there are also approaches integrating CBR into other techniques [20–25].

In designing sustainable products, CBR can be applied in product life cycle assessment [26] and establishing eco-design support [27,28]. The latter is accomplished by utilizing fuzzy set theory to discern the design attributes for product case retrieval [28], or to predict the transport, environmental, end-of-life, and economic costs of the new product [27]. Unfortunately, there is little research on the employment of CBR in selecting the input variables for the specification of parametric models and their application in simulations to achieve product sustainability targets.

2.3. Simulations for Achieving Product Sustainability Targets

Achieving product sustainability targets can be aided by searching for possible ways of developing a product to fit within given design, economic, safety and environmental limitations. This is a particularly important task if there is a risk of failing to achieve the targets. Simulations can be an effective tool for identifying possible ways to achieve product sustainability targets. Simulations are used in various areas of business, such as manufacturing [29,30], product life cycle assessment [31], and business process modeling [32].

The current literature is mostly devoted to simulations of product sustainability in areas such as design, manufacturing, and logistics [33–38]. Specific concepts related to these areas include reverse engineering, reverse logistics, and target costing. Design-related issues are often approached from an engineering perspective, including reverse-engineering simulations that help extract valuable information from an existing object for the purpose of creating a model of the object. Reverse engineering can use three-dimensional scanning and CAD software for modeling objects; three-dimensional printing for making product prototypes; and CAE software for carrying out simulations for mechanical analysis and the validation of kinematics [39,40].

Reverse logistics involves tracing flows of materials backward, packaging and finished goods from a place of consumption to a place of remanufacture, repair, refurbishing or reuse, and the relevant recycling or disposal of the aforementioned packaging materials and goods [41]. A review of the literature on the interrelationships of reverse logistics and sustainability performance is presented in [42]. Moreover, the operational excellence of sustainable reverse supply chains in a circular economy is presented in [43]. In addition, a network design model of reverse logistics dedicated to product reuse and recycling within environmental limitations is proposed in [44], and a reverse logistics methodology designed to increase sustainability in a supply chain is set out in [45,46]. The employment of reverse logistics for product reuse, remanufacturing, recycling, and refurbishing is considered in [47–49].

Simulations may also be successfully used to search for ways of reaching the target level of costs related to a sustainable product. The process of target costing involves determining the product cost for which the desired functionality, quality, sustainability, and profit margin can be achieved. As these product features may be easily modified during product design, target costing is particularly useful at the beginning of product development. The aspect of reducing the total cost of a new product at the product design stage is presented in [50]. Cost prediction for the entire product life cycle plays a key role in increasing the chances of developing a successful product and achieving business competitiveness.

The product design process addresses several problems that should be solved by an effective R&D team. These problems include technological, organizational, and environmental issues regarding the new product. Problem solving in product design can be effectively supported by simulations that enable the identification of possible changes that could increase product sustainability within the model specification of the considered problem. This model can be described using the variables, domains, and constraints based on which simulations are performed.

3. The Proposed Approach to Achieving Sustainability Targets of New Products

The proposed approach is based on the application of CBR methodology. It is designed to address the needs of R&D staff members. It supports them in assessing the sustainability of a new product and identifying potential problems related to achieving sustainability targets at different product life stages (from design to recycling or disposal). Moreover, the proposed approach identifies possible solutions through which product sustainability targets can be achieved. These solutions aim to attain the target level of product sustainability through changes introduced in the new product development process. The mentioned changes should improve the product's sustainability in environmental, economic, and social terms.

The proposed approach includes the following stages:

1. Assessing the sustainability of the new product using data on similar products stored in company databases; determining sustainability targets for the new product;
2. Using CBR for model specification and to identify solutions to product design problems; applying parametric modeling to determine the relationships needed in simulations;
3. Identifying opportunities to achieve sustainability targets of the new product.

Figure 2 presents a framework for the proposed approach that can be divided into three areas: assessing sustainability, identifying relationships and performing simulations. The latter is related to supporting designers in finding opportunities to increase product sustainability and achieve sustainability targets. Further sections discuss these three areas in more detail.

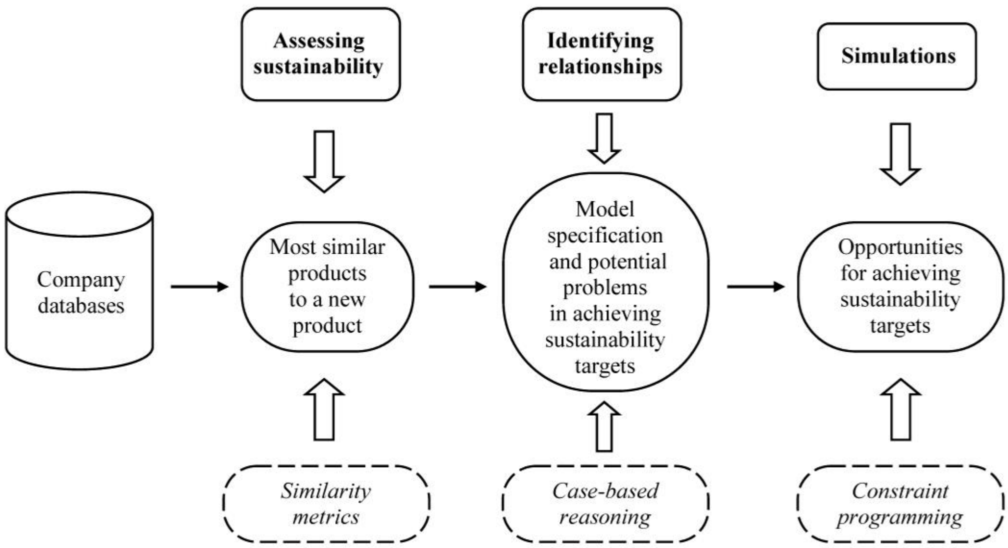

Figure 2. A framework that supports sustainable product design.

3.1. Data Collection and Assessing Product Sustainability

Data collection involves the retrieval from company databases of the cases that are the most similar to the new product. These cases are selected from among previous products that belong to the same product line as the new product and have the most similar features. Company databases register many business processes, such as product design, procurement, manufacturing, warehouse management, sales and marketing, accounting, and after-sales services. The last of these is an issue that can be impacted by the use of poor-quality materials and components as well as improper design. The product design process is often supported by employing information systems such as computer-aided design and computer-aided engineering. In turn, business processes related to production, sales, procurement, warehousing, and accounting are recorded by ERP systems. These systems aid employees in managing manufacturing operations and information regarding, for example, customers and products. Another valuable information system is that related to customer relationship management. This system holds information on customer complaints regarding product usage, expectations of product functionality, or the incidence of faulty products. Company databases can also store the experiences of R&D staff in the design process—for instance, the recognized limitations of product recycling or disposal.

In this study, product sustainability is evaluated with the use of an analogical technique. This technique is based on a similarity analysis that compares previous products to the new product. The similarity analysis includes the selection of several product features—for example, size, weight, or materials used in the manufacturing process. The selection of similar cases is determined by the calculation of two measures: the similarity function (1) and the similarity value (2).

$$SF_i = 1 - \frac{\left|f_i^N - f_i^P\right|}{max(f_i)} \tag{1}$$

$$SV = \frac{\sum_{i=1}^{n} w_i \times SF_i}{\sum_{i=1}^{n} w_i} \tag{2}$$

where f_i^N and f_i^P are values of the i-th feature for the new and previous product, respectively, whereas w_i is the weight of the i-th feature.

Real values of the i-th feature f_i^N and f_i^P are normalized to values between 0 and 1. The sum of weights for n features equals 1. The choice of a previous product that is the most similar to the new one is determined according to the weighted average depending on the importance of the i-th feature.

Product sustainability evaluation requires the selection of criteria for assessment that can refer to general issues of sustainability (e.g., the adverse environmental impact measured in the CO_2 footprint) or issues regarding the product type (e.g., energy consumption for electrical devices, or battery longevity for smartphones). Commonly used criteria of assessing product sustainability include resource consumption (e.g., raw materials, water, energy) for production and/or product usage, product lifespan, and recycling rate.

The proposed approach can also predict the financial performance of a new product—for example, its cost and revenue. Here, predicted financial values must be adjusted for inflation, particularly for long-term periods. If the predicted sustainability for the new product is unsatisfactory to the company's top management, they may set out sustainability targets for this product. Achieving sustainability targets involves overcoming many problems to which solutions may be found by applying CBR methodology. The next subsection presents the application of this methodology. It describes the model specification required to carry out simulations that identify opportunities to achieve sustainability targets.

3.2. CBR for Identifying Solutions to Problems in Eco-Design and Model Specification

In this study, the CBR methodology is applied to finding a solution to a problem and specifying input variables for a parametric model. The problem is one of product sustainability improvement.

Company databases contain vast amounts of data regarding business processes and product designs and specifications. Our CBR methodology seeks to identify past cases identical or similar to the one at hand stored in company databases and use them to solve problems presented by the new case. CBR consists of the following six stages [51]:

1. Identifying the problem at hand;
2. Specifying the variables (product features) that define the problem;
3. Searching for previous cases similar to the case at hand;
4. Finding solutions to the problem at hand based on previous cases;
5. Assessing the feasibility of the solutions;
6. Adding the chosen solution to the case case base to increase its potential of solving future problems.

The CBR methodology is often considered as a cycle that includes phases such as retrieval, reuse, revision, and retention [51]. The retrieval phase involves searching the case case base for cases resolving a problem similar to the problem at hand. The problem to be considered is defined by a set of variables, which are then used to identify the most similar cases. The retrieved cases are then further evaluated using the similarity function. Finally, a search is conducted for potential problems that may appear in the new case, and solutions to these problems are identified.

The next phase involves reusing the identified solution to the current problem. If the problem solved in the previous case only matches the problem at hand to a certain extent, the identified solution is suboptimal, and it should be revised.

The third phase of this cycle is revision, which involves adjusting parameters of the retrieved solution to conform it to the problem at hand. This phase usually needs additional information to be specified through parametric models, rules, or domain knowledge [51].

The last phase of the CBR cycle is retention. Here, the verified solution is added to the case case base. It must be underlined that only solutions with the potential to improve the future solution of the specific problem (e.g., the design problem) should be stored.

The second area of CBR usage is one wherein input variables are specified to the applied parametric model. Accordingly, the set of input variables is reduced to the variables that have a strong direct impact on the output variable (correlation coefficient larger than 0.7). Such input variables should have controllable properties to facilitate changes initiated by top management to improve product sustainability. An example of a controllable input variable is the number of prototype tests that are correlated with the product failure rate. Of importance is that the data retrieved and applied in the analysis should belong to products from the same line as the new product.

The selection of input variables and related data depends on the specific problem. For example, if the output variable is the product life cycle, then input variables may refer to the quality of materials needed for production, prototype tests, or the time and expenditures related to product design. The identified relationships between input and output variables should indicate opportunities for increasing product sustainability.

In this study, the parametric modeling involves the use of regression analysis and artificial neural networks. Regression analysis provides linear or nonlinear models for predicting or inferring causal relationships. Artificial neural networks are based on a nature-inspired methodology that was developed to solve complex real-world problems that cannot be solved using only traditional modeling. The advantages of applying regression analysis are its ease of implementation and lower computational power requirements. Artificial neural networks are especially useful in identifying nonlinear complex relationships.

Parametric models are compared according to the mean absolute percentage error (MAPE) as follows:

$$MAPE(\%) = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_t - p_t}{x_t}\right| \tag{3}$$

where x_t and p_t are the actual and predicted values, respectively, and n is the number of input-output pairs.

Predictions are verified by dividing the data into training and testing sets. The experiments are performed with the use of k-fold cross-validation, where the results are calculated as the average of k folds. Cross-validation is a resampling method in which k iterations are carried out for various data subsets. Finally, predictions are determined using the parametric model for which the least MAPE in the testing set was obtained.

3.3. Simulations for Achieving Sustainability Targets

The identified parametric models are used to perform simulations and find opportunities to enhance product sustainability. Such simulations are performed within a specified model that consists of variables and constraints, including domains of variables and relationships between variables. This study aims to find opportunities to increase product sustainability. These opportunities can be linked to possible changes in product design with the potential to increase product sustainability. In this study, the problem of improving product sustainability is specified in terms of constraint-satisfaction modeling. This modeling facilitates the specification of a simulation environment, describing it through sets related to variables $\{V_1, V_2, \ldots, V_n\}$, discrete domains $\{D_1, D_2, \ldots, D_n\}$ of variables V, and constraints $\{C_1, C_2, \ldots, C_m\}$.

A constraint-satisfaction model may be formulated as a finite and discrete domain of values that are associated with each variable. A constraint is a relationship applicable to a subset of variables. Formulating a problem through constraint-satisfaction modeling is an effective way of identifying a solution (if any) to the problem under consideration. A solution to a constraint-satisfaction problem is a state for which all constraints are fulfilled. To achieve this state, learning mechanisms are applied to pruning the search space [52]. Consequently, constraint-satisfaction modeling improves algorithmic techniques dedicated to solving real-life problems [53].

A set of possible solutions reflects admissible changes in product design, depending on the scope of variables, their domains, and constraints. These may be interrelated variables. Constraints are the limitations regarding, for example, technological issues (e.g., the minimal density of materials) and scarce resources (e.g., R&D specialists). The problem being specified as CSM helps R&D staff to obtain information about product sustainability and the conditions in which the sustainability targets of a new product could be achieved. Solving the above-described problem involves finding answers to the following questions:

- What is the predicted level of product sustainability for the new product?
- Are there any opportunities in the product design process that will improve product sustainability and achieve the sustainability targets set for the new product?

In this study, constraint-satisfaction modeling is implemented within a constraint programming environment in which constraint propagation and search algorithms are employed. This environment makes it much easier to find a solution to a constraint-satisfaction problem (CSP) according to constraint propagation, or to demonstrate that the CSP does not have a solution [54]. Constraint propagation can repeatedly reduce domains and/or constraints during its performance. The constraint programming (CP) technique is particularly effective when compared to an exhaustive search. An exhaustive search always finds a solution (if one exists), but its performance is inversely proportional to the number of admissible solutions. An exhaustive search tends to vastly increase the number of solutions, which limits its feasibility in many practical problems [55]. The utility of CP consists in the enormous reduction of the computational time required compared to an exhaustive search. It is especially significant in cases in which the search space is vast and all admissible solutions should be found.

4. Applicability of the Proposed Approach

The below-presented example illustrates the applicability of the proposed approach. It consists of three parts: (1) using similarity analysis for assessing product sustainability; (2) using CBR for model specification and to find solutions to problems occurring in product design; (3) using simulations for achieving sustainability targets. The example refers to the improvement of product sustainability measured by expanding the product life cycle (output variable) through changes incorporated in the design process (input variables). These changes are intended to increase long-term product use and, ultimately, product sustainability.

The example involves a line of robot vacuum cleaners. These household devices are increasingly popular. Their advantages, compared to traditional cleaning, include scheduling and tracking capabilities, automatic docking and recharge, cordless design, cleaning under furniture, and remote-control functions that are useful for people with limited mobility. Conversely, the robots' disadvantages include the risk of becoming stuck or flipping over, frequent dust bin changes, long cleaning times, short battery lifespan, and uselessness on stairs and higher surfaces [56,57]. The design of this product type may be divided into three dimensions: mechanical, electrical, and software [56]. The example provided here involves mechanical and electrical changes made to improve product sustainability. Changes in the mechanical dimension are intended to reduce the product failure rate (V_1), and consequently increase its longevity. Changes in the electrical dimension were made to extend battery lifespan (V_2). Reducing the number of battery replacements and the number of defective products extends the product life cycle and improves its sustainability performance in environmental, economic, and social terms.

4.1. Similarity Analysis for Assessing Product Sustainability

A company is planning to develop a new product (P_A) that should include new features not shared by current products. These features are meant to improve the product's sustainability as measured by V_1 and V_2. First, selected criteria are set out for assessing product sustainability. These criteria are product features such as size, weight, functionality, components, drivers, and sensors. Secondly, similarity analysis is applied to identify the existing product that is the most similar to the new product. Table 1 presents the values for selected features and similarity functions (SF) for the new and previous product.

Table 1. Similarity functions.

Feature	f^N	f^P	SF
Size	34	34	1.000
Weight	3.3	3.2	0.970
Number of functionalities	17	16	0.941
Number of components	33	31	0.939
Number of drivers and sensors	8	7	0.875

If product features are of the same importance, then the arithmetic mean of similarity functions is used to calculate the similarity value (SV). According to Formula (2), SV equals 0.945 for the similarity functions presented in Table 1. In the next step, the values of product sustainability V_1 and V_2 are sought. Table 2 presents the similarity values (in descending order) and product sustainability for the most similar products.

Table 2. The similarity values and product sustainability.

Product	SV	V_1	V_2
P_B	0.945	18	350
P_C	0.916	20	350
P_D	0.872	20	300
P_E	0.870	21	250
P_F	0.833	21	250

The level of product sustainability is predicted using the values for the most similar product (P_B). It is V_1 = 18 and V_2 = 350. However, this level is unsatisfactory to the top management, who have set out the following sustainability targets: V_1 = 16 and V_2 = 400. The next subsection illustrates the use of CBR for model specification and identifying solutions to the problem of improving product sustainability.

4.2. CBR for Supporting Eco-Design and Model Specification

In this study, the use of CBR embraces two areas: (1) finding a previous case that provides a workable solution to the problem at hand; and (2) specifying input variables for a parametric model. The problem is one of improving product sustainability. In the presented example, the improvement of product sustainability is defined as reducing the product failure rate (V_1) and extending the battery lifespan (V_2). Finally, the application of CBR is intended to enable the finding of solutions that were used to solve similar problems in the past and are registered in the company's databases. For example, CBR makes it possible to find ways of extending battery lifespan by changing the materials used in battery cells (e.g., lithium-ion instead of nickel metal hydride), providing a larger battery, or reducing the product's weight. Moreover, CBR can identify solutions used in designing past R&D projects to reconcile occasionally-conflicting requirements (e.g., larger size and weight reduction). The product failure rate can be reduced through, for example, improving the quality of materials and components employed in fabricating the robot vacuum cleaners, or by extending the battery capacity and performing prototype tests. It is worthy of note that the product failure rate depends not only on the manufacturer but also on the conditions of product use by the consumer (e.g., the frequency of use and the size and type of surface cleaned).

The second area of CBR application includes selecting the variables that will be input into the parametric model. For example, CBR can identify solutions to the problem of a high product failure rate (V_1) and select input variables that were used in the past to surmount this problem. These variables can include elements of product design and specification and include the number of prototype tests, components, drivers, sensors, moving parts, brushes, product functionalities, the density of materials used in the manufactured casing, and product weight, size, or power. In the next step, the set of input variables is reduced using two criteria: strong direct impact of an input variable on an output variable (correlation coefficient larger than 0.7), and the above-mentioned controllable properties of the input variable. For example, the number of prototype tests is a more controllable variable in the new product development (NPD) process than the number of product components. The set of output (V_1–V_2) and input (V_3–V_8) variables is as follows:

V_1—the product failure rate (the number of failures per 1000 new products);
V_2—the battery lifespan (in charge-discharge cycles);
V_3—the number of prototype tests;
V_4—the number of R&D staff members involved in the NPD project;
V_5—the material density of manufactured casings (in g/cm^3);
V_6—the product weight (in kg);
V_7—the battery size (in cm^3);
V_8—the battery capacity (in Ah).

The model specification for the product failure rate (4) and battery lifespan (5) is determined as follows:

$$V_1 = f\ (V_3, V_4, V_5) \tag{4}$$

$$V_2 = f\ (V_6, V_7, V_8) \tag{5}$$

These relationships were determined using data related to the most similar previous products that belong to the same line as the new product. The dataset was divided into training and testing sets to select a model with the best ability for generalization. The training set consists of records for 15 products and the testing set is for 4 products. Parametric models were compared using their MAPEs (3), which were calculated as the arithmetic mean for the 5-fold cross validation. Relationships (4) and (5) were specified using linear regression (LR), nonlinear regression (namely, the polynomial model—PM), and artificial neural networks (NN). The latter were trained using two algorithms: the gradient descent with momentum and adaptive learning rate backpropagation (NN-GD), and Levenberg–Marquardt backpropagation (NN-LM). Table 3 shows the MAPEs in the training and testing sets for different parametric models.

The results shown in Table 3 indicate that NNs provide smaller MAPEs in the training and testing sets in comparison with linear and nonlinear regression models. The smallest MAPEs in the testing set, both for V_1 and V_2, were provided using the NN-GD model. Consequently, this model was selected for use in simulations to identify ways of achieving sustainability targets for the new product.

Table 3. The comparison of MAPEs for parametric models (in %).

Output Variable	Parametric Model	Training Set	Testing Set
V_1	LR	14.02	15.69
	PM	12.62	14.32
	NN-GD	11.37	12.91
	NN-LM	7.97	13.54
V_2	LR	12.63	14.03
	PM	11.43	12.86
	NN-GD	10.04	11.59
	NN-LM	6.73	12.53

4.3. Simulations for Achieving Sustainability Targets

Simulations were performed using the constraint programming environment. Constraints can include available resources (e.g., R&D staff) and technological issues (e.g., minimum battery capacity). The aim of the simulations is to identify possibilities (if any) of achieving sustainability targets through changes in input variables that are related to product features, including product design, tests, manufacturing, and use. The sustainability targets for the new product are as follows: $V_1 \leq 16$ and $V_2 \geq 400$. Simulations were performed for the following domains of input variables: $D_3 = \{25, 26, \ldots, 35\}$, $D_4 = \{3, 4, 5\}$, $D_5 = \{7.4, 7.5, \ldots, 8.7\}$, $D_6 = \{8.5, 8.6, \ldots, 10.5\}$, $D_7 = \{270, 271, \ldots, 295\}$, and $D_8 = \{1.8, 1.9, \ldots, 3.5\}$. Selected results of simulations regarding product sustainability improvement are provided in Table 4.

Table 4. Simulation results.

Input Variables	Output Variables
$V_3 = 35$, $V_4 = 5$, $V_5 = 8.5$, $V_6 = 9.5$, $V_7 = 290$, $V_8 = 3.2$	$V_1 = 16$, $V_2 = 400$
...	...
$V_3 = 35$, $V_4 = 5$, $V_5 = 8.5$, $V_6 = 9.5$, $V_7 = 290$, $V_8 = 3.5$	$V_1 = 16$, $V_2 = 422$
...	...
$V_3 = 35$, $V_4 = 5$, $V_5 = 8.5$, $V_6 = 9.5$, $V_7 = 291$, $V_8 = 3.2$	$V_1 = 16$, $V_2 = 402$
...	...
$V_3 = 35$, $V_4 = 5$, $V_5 = 8.5$, $V_6 = 9.5$, $V_7 = 291$, $V_8 = 3.5$	$V_1 = 16$, $V_2 = 424$
...	...
$V_3 = 35$, $V_4 = 5$, $V_5 = 8.5$, $V_6 = 9.4$, $V_7 = 290$, $V_8 = 3.2$	$V_1 = 16$, $V_2 = 404$
...	...
$V_3 = 35$, $V_4 = 5$, $V_5 = 8.5$, $V_6 = 9.4$, $V_7 = 290$, $V_8 = 3.5$	$V_1 = 16$, $V_2 = 426$
...	...
$V_3 = 35$, $V_4 = 5$, $V_5 = 8.6$, $V_6 = 9.5$, $V_7 = 290$, $V_8 = 3.2$	$V_1 = 16$, $V_2 = 400$
$V_3 = 35$, $V_4 = 5$, $V_5 = 8.7$, $V_6 = 9.5$, $V_7 = 290$, $V_8 = 3.2$	$V_1 = 15$, $V_2 = 400$
...	...
$V_3 = 35$, $V_4 = 5$, $V_5 = 8.7$, $V_6 = 8.5$, $V_7 = 295$, $V_8 = 3.5$	$V_1 = 15$, $V_2 = 466$

The number of all possible solutions in the above domains is 9,417,408. Using a constraint programming technique, this number was reduced to a set of 792 admissible solutions, several of which are presented in Table 4. The achievement of sustainability targets is predicted for the maximum number of prototype tests ($V_3 = 35$) and R&D staff members ($V_4 = 5$). The product weight (V_6) has a negative impact on the number of battery charge-discharge cycles (V_2). The most significant positive impact on output variables is the battery capacity (V_8). An increase in material density influences product weight, leading to a short battery lifespan. The most advantageous result ($V_1 = 15$ and $V_2 = 466$, presented in the last row in Table 4) was obtained for the greatest admissible material density ($V_5 = 8.7$) and the smallest admissible product weight ($V_6 = 8.5$). These values can guide the further work of R&D staff.

The presented results of simulations can support designers in the NPD process and product specification by providing them with information about, for example, battery capacity and size, which can be used to extend product longevity. The obtained information is based on the specifications of past products, and the proposed solutions for the new product may lead to new problems, which can in turn be solved by testing prototypes or using the CBR approach. For example, CBR can be applied to identify possible solutions to the problem of increasing the battery size and reducing the product's weight. If this problem has occurred in the past, the company databases can be used to select products for which a solution to the current problem was found. It is noteworthy that the proposed approach provides all possible solutions (if any) to the problem of achieving the sustainability targets of the new product.

The presented approach may also be employed to obtain information about prerequisites to reaching sustainability targets. For instance, about the value that input variables should have so as to increase the battery lifespan to 500 charge-discharge cycles and reduce the product failure rate to 12. Table 5 presents a few scenarios offering potential ways to meet the above-mentioned targets.

Table 5. Scenario analysis.

Scenario	Input Variables	Output Variables
Basic scenario	$V_3 = 35$, $V_4 = 5$, $V_5 = 8.7$	$V_1 = 15$
Changes for V_3	$V_3 = 37$, $V_4 = 5$, $V_5 = 8.7$	$V_1 = 12$
Changes for V_4	$V_3 = 35$, $V_4 = 6$, $V_5 = 8.7$	$V_1 = 12$
Changes for V_5	$V_3 = 35$, $V_4 = 5$, $V_5 = 10.9$	$V_1 = 12$
Basic scenario	$V_6 = 8.5$, $V_7 = 295$, $V_8 = 3.5$	$V_2 = 466$
Changes for V_6	$V_6 = 7.5$, $V_7 = 295$, $V_8 = 3.5$	$V_2 = 501$
Changes for V_7	$V_6 = 8.5$, $V_7 = 315$, $V_8 = 3.5$	$V_2 = 500$
Changes for V_8	$V_6 = 8.5$, $V_7 = 295$, $V_8 = 4.0$	$V_2 = 503$

The basic scenarios presented in Table 5 refer to the values from the last row of Table 4, which provides the best case for accessible resources. The results presented in Table 5 may guide the future research of R&D specialists. Scenario analysis is closely interrelated with sensitivity analysis. Figure 3 illustrates to what degree the input variable influences the output variable.

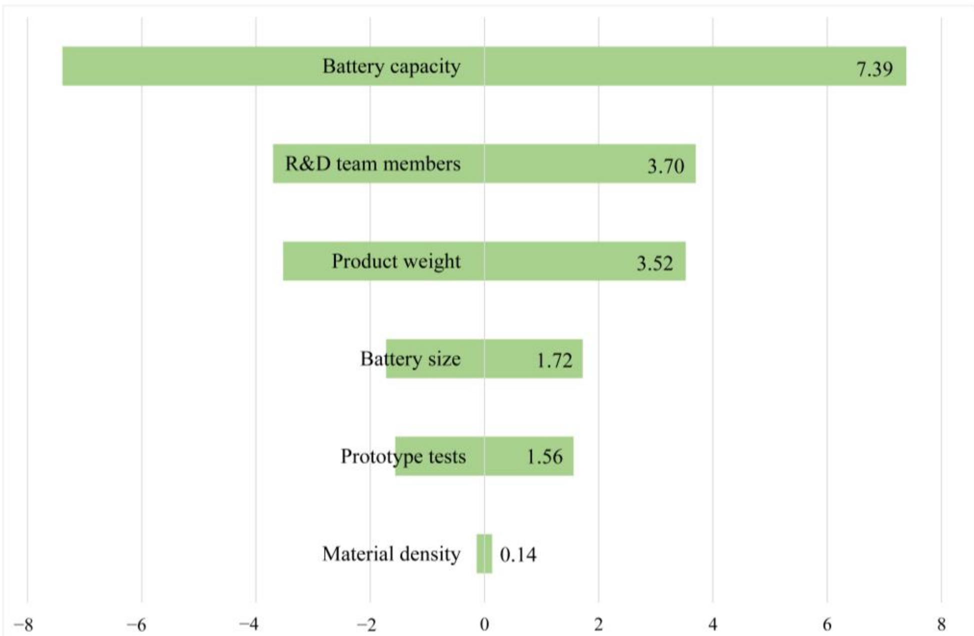

Figure 3. Tornado chart for input variables.

The strongest increase of the battery's lifespan is caused by the increase of the battery's capacity. Each unit increase of the battery capacity (0.1 Ah) extends the battery lifespan by about 7 charge-discharge cycles. The strongest impact on reducing the product failure rate is obtained by increasing the number of R&D staff members. The selection of variable(s) for simulations can be performed by an R&D staff member intentionally or by using sensitivity analysis as incorporated into a decision-support system.

The scenario analysis presented in Table 5 requires extended domains for input variables, as follows: D_3 = {25, 26, . . ., 37}, D_4 = {3, . . ., 6}, D_5 = {7.4, 7.5, . . ., 11.0}, D_6 = {7.5, 8.6, . . ., 10.5}, D_7 = {270, 271, . . ., 315}, and D_8 = {1.8, 1.9, . . ., 4.0}. The enlargement of the domains increases the number of choice nodes in the search tree. Consequently, there is a need for an effective technique of identifying admissible solutions in the search space.

Table 6 illustrates the time needed for finding admissible solutions using an exhaustive search (ES) and constraint programming (CP) as strategies of variable distribution. There are two cases for the smaller and greater search space related to domains and results. These are presented in Tables 4 and 5, respectively.

Table 6. Comparison of different search strategies.

Case	Search Strategy	Nodes Checked	Time [s]
1	ES	2376	0.27
	CP Naïve	792	0.07
	CP First-fail	792	0.05
	CP Split	792	0.05
2	ES	76,032	6.54
	CP Naïve	25,344	1.62
	CP First-fail	25,344	1.47
	CP Split	25,344	1.38

The results confirm the advantage of using CP over an exhaustive search in terms of reducing the computational time. This is particularly important given a vast search space. CP significantly reduces the number of admissible solutions and the time needed to search for them. The extended domains may result in providing a huge set of very similar solutions. A decision-support system can show all solutions or just one optimal solution, according to user preferences. The set of solutions can also be reduced by taking into account only the minimum and maximum values of domains.

5. Discussion

The proposed approach aims to ease the R&D task load, particularly in designing a sustainable product. This support involves: (1) using a CBR methodology to identify solutions to design-related problems and model specification; and (2) using constraint programming to run simulations to identify opportunities to achieve sustainability targets set for the new product.

The first way of employing the proposed approach involves supporting the development of eco-products. CBR methodology is commonly applied to retrieve a suitable case from the company database and use previous experiences to resolve the problem at hand. The widespread application of CBR is due to its broad practicability. With regard to sustainability-related issues, CBR is often applied in sustainable urban development [58–60], making green retrofit decisions [61,62], developing practical renewable energy projects [63,64], and design [65–67]. Moreover, there is some research on merging CBR with other techniques to enhance their properties. Romli et al. [27], for example, proposes combining CBR with quality function deployment in the cost estimation and life cycle assessment of medical forceps. Ren et al. [28] merges CBR methodology with fuzzy set theory to increase the efficiency of case retrieval and, ultimately, support vacuum pump design. There is also widespread integration of TRIZ with CBR and LCA methods for supporting the design of eco-products (mobile phone displays and cooker hoods) [51,68].

Compared to the previous research, our study enhances CBR methodology through the use of regression analysis and NNs to define models for finding relationships between variables that significantly affect product sustainability. Consequently, the proposed approach enhances CBR methodology not only with regard to retrieving and reusing cases from the company database but also in terms of revising a previous case into a new one.

The second application of the proposed approach is to performing simulations to search for ways of enhancing product sustainability. Simulations are mainly employed in the area of manufacturing system design [29,30,69] and assessing a product's life cycle [31,70,71]. After assessing a product's life cycle, its resource and energy consumption can be calculated, as can environmental impacts and economic predictions. These studies usually involve the integration of LCA with sustainable product development with an eye toward identifying the parameters of an optimal manufacturing or design process. There is a lack of studies on identifying conditions in which sustainability targets of the new product could be achieved. Our study presents the use of constraint programming within constraint-satisfaction modeling to find a solution to the problem of identifying opportunities for improving product sustainability and consequently for achieving the sustainability targets of a new product.

This study may also be considered from the perspective of enhancing product reliability, durability, and longevity, ultimately increasing product sustainability by reducing the consumer's need to buy a new product. Previous studies were devoted to the improvement of product reliability in the context of increasing customer satisfaction [72–74]. Jamnia and Atua [75], for example, present return on investment and the costs of unreliability in the product life cycle and indicate the importance of reliability modeling and planning. Our study has further developed the previous approaches to finding levels of product reliability that promote the achievement of sustainability targets.

6. Conclusions

The proposed approach has been developed to support R&D staff members in identifying product design opportunities which could promote the achievement of product sustainability targets. The improvement of product sustainability considered in this research is tied to the reduction of the product failure rate.

The main contribution of this study is the application of case-based reasoning methodology for identifying solutions to problems that arise at the design stage, assessing product sustainability, and applying constraint-satisfaction modeling to the process of exploring and utilizing all possible opportunities (if any) to achieve sustainability targets. The problem specification in terms of CSM facilitates the use of constraint programming and reduces the search space and computational time. This enables the development of an interactive decision support system dedicated to the issue of product sustainability improvement. Here, the application of CSM facilitates an expansion of the model toward specifying another optimization or decision problem—for example, finding trade-offs between economic and environmental benefits.

Constraint-satisfaction modeling enables R&D staff members to become familiar with all possible changes in the product design process that could result in improvements to product sustainability. These changes may be something novel and surprising for R&D staff members, revealing new avenues for product modifications. On the other hand, the application of CSM may generate vast solution spaces for which the human ability to interpret results is limited. This may be seen as a limitation of the proposed approach, warranting further research. Future research may also be focused on obtaining information from potential consumers by surveying their purchasing preferences in terms of, for example, desirable product functionality, price, and product sustainability, and using this information to create concepts for a new product. An additional limitation of the proposed approach may lie in the possible absence of data on similar product specifications. Since CBR methodology and regression analysis are data-driven approaches, the more cases that are available, the more reliably they can be used. Moreover, the proposed approach is designed to support R&D staff in developing successive modifications of existing products instead of developing entirely new products.

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