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A Data-Driven Approach for Improving Sustainable Product Development

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Abstract: A product's impact on environmental issues in its complete life cycle is significantly determined by decisions taken during product development. Thus, it is of vital importance to integrate a sustainability perspective in methods and tools for product development. The paper aims at the development of a method based on a data-driven approach, which is dedicated to identifying opportunities for improving product sustainability at the design stage. The proposed method consists of two main parts: predictive analytics and simulations. Predictive analytics use parametric models to identify relationships within product sustainability. In turn, simulations are performed using a constraint programming technique, which enables the identification of all possible solutions (if there are any) to a constraint satisfaction problem. These solutions support R&D specialists in finding improvement opportunities for eco-design related to reducing harmful impacts on the environment in the manufacturing, product use, and post-use stages. The results indicate that constraint-satisfaction modeling is a pertinent framework for searching for admissible changes at the design stage to improve sustainable product development within the full scope of socio-ecological sustainability. The applicability of the proposed approach is verified through an illustrative example which refers to reducing the number of defective products and quantity of energy consumption.

Keywords: constraint-satisfaction modeling; eco-friendly products; energy consumption; predictive analytics; product sustainability; sustainability performance; systems modeling and simulation

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1. Introduction

At present, the improvement of sustainability performance is a common tendency resulting from the environmental, economic and societal aspects. Environmental regulations, customer ecological awareness, and perceptions of corporate social responsibility result in increasing interest in product sustainability among manufacturing companies. Designing eco-friendly products can require using new materials and technologies (for example, in reducing energy consumption), which usually increase the cost of a new product but from a long-term perspective, they can boost company profits.

Product design is a crucial process in improving product sustainability and, ultimately, customer satisfaction through using fewer energy-intensive or defective products. Moreover, product design can reduce the cost of manufacturing and product usage through creating suitable changes in product features. Some changes towards improving product sustainability can refer to a number of stages of the product life cycle, resulting in a large impact on the environment. For example, better quality of materials can result in reducing the number of defective products in manufacturing and greater reliability in the product usage stage. It is noteworthy that a product's usage is usually longer than its manufacturing. As a result, sustainability improvement in the product usage stage seems to be of significant importance. In this case, changes incorporated into a product at the design stage can significantly improve product sustainability, such as through using effective energy solutions or recyclable materials. Identifying improvement opportunities in product design seems to be particularly important in the household appliance industry, which provides energy-intensive products that are often intended for long-term use.

Currently, companies register their business processes in databases related to information systems. Product design can be supported by software related to computer-aided design and engineering. In turn, processes related to manufacturing are supported by enterprise resource planning systems and computer-aided manufacturing systems. In addition, customer complaints and requirements can be registered in customer relationship management systems. Consequently, data stored in company databases can be used to obtain information for specialists in the research and development (R&D) department to improve product sustainability. For this reason, a data-driven approach is proposed for evaluating sustainability performance, identifying relationships, and carrying out simulations that aim to improve sustainability performance.

Product design is often related to product configuration tasks that can be solved using a constraint satisfaction problem (CSP) [1–3]. Constraint satisfaction modelling is also effectively used in the conceptual design phase [4,5] and life cycle cost [6,7]. However, constraint satisfaction modelling is rarely used within sustainable development. CSPs appear mainly in the literature in the context of sustainable supply chain-management applications [8]. The aspect of improving the sustainability performance of household appliances through changes incorporated during product design has not yet been investigated. This is motivation for elaborating on an approach to support R&D specialists towards providing information about suitable changes at the product design stage, for which sustainability performance could be improved in further stages of the product's life cycle. The novelty of this study can be considered in the context of using constraint satisfaction modeling to address problem formulation and elaborating on a method addressed to the following fields: (i) predicting sustainability performance and (ii) searching for improvement opportunities within product design to enhance sustainability performance in the stages of manufacturing and product usage. As a result, the method enables an R&D department to receive information regarding possible changes in product design, if there are any. These changes can refer, for example, to reducing the number of defective products in manufacturing and energy consumption in product usage.

This study aims to develop a method based on a data-driven approach and is dedicated to identifying opportunities for improving product sustainability at the product design stage. The proposed method integrates areas of sustainability performance evaluation, identification of relationships between factors affecting product sustainability, and simulations of changes in product design, by which sustainability performance can be improved. A data-driven approach uses regression analysis to identify relationships that are further applied to predicting and simulating sustainability performance. The contribution is related to problem formulation in terms of a CSP, in which constraint programming is applied to an effective search of possible solutions. The time-effective identification of possible solutions is particularly significant in a large search space, which can result from the number of variables involved in a simulation model and the granularity of their domains. The advantage of the proposed approach is in identifying all admissible changes in the design process (if there are any) by which desirable sustainability performance for a new product can be reached. The results of experiments indicate that constraint-satisfaction modeling enables the specification of socio-ecological sustainability while obtaining answers to questions about sustainability performance evaluation and finding prerequisites for achieving the required level of sustainability performance.

The paper consists of five sections that include the introduction, literature review, proposed method, illustrative example, and conclusion. Section 2 includes a literature review in the following fields: product sustainability, data-driven approaches for sustainable product development, and a reverse approach for supporting product sustainability. The proposed method of predicting product sustainability and identifying possible changes at the product design stage for improving sustainability performance is illustrated in Section 3. The applicability of the proposed method based on the data-driven approach is presented in Section 4. Sections 3 and 4 refer to concepts such as predictive analytics and simulations for improving product sustainability. Finally, the conclusion and suggestions for further research are presented in Section 5.

2. Literature Review

2.1. Sustainable Product Development

The main concept of sustainability, or sustainable development, is related to finding the triple trade-off between achieving environmental cleanliness, economic success, and social responsibility. From a company perspective, sustainability can be seen as the meeting point between environmental concerns, manufacturing, and design activities [9]. However, product sustainability should consider not only in terms of designing, manufacturing, and using the product, but also consumer utilization, ultimate reuse, recycling, and remanufacturing [10]. The subsequent post-uses of the product lead to the concept of multiple life cycles which in turn induce closed-loop flow [11]. A pivotal element of closed-loop flow is the 6R concept that encompasses reduction, reuse, recycling, recovery, redesign, and remanufacture. Closed-loop production systems try to find an efficient way to enhance the flow of materials, components, energy, and other resources throughout multiple life cycles of the product [12]. The 6R concept placed in an environmental and socio-economical system is presented in Figure 1.

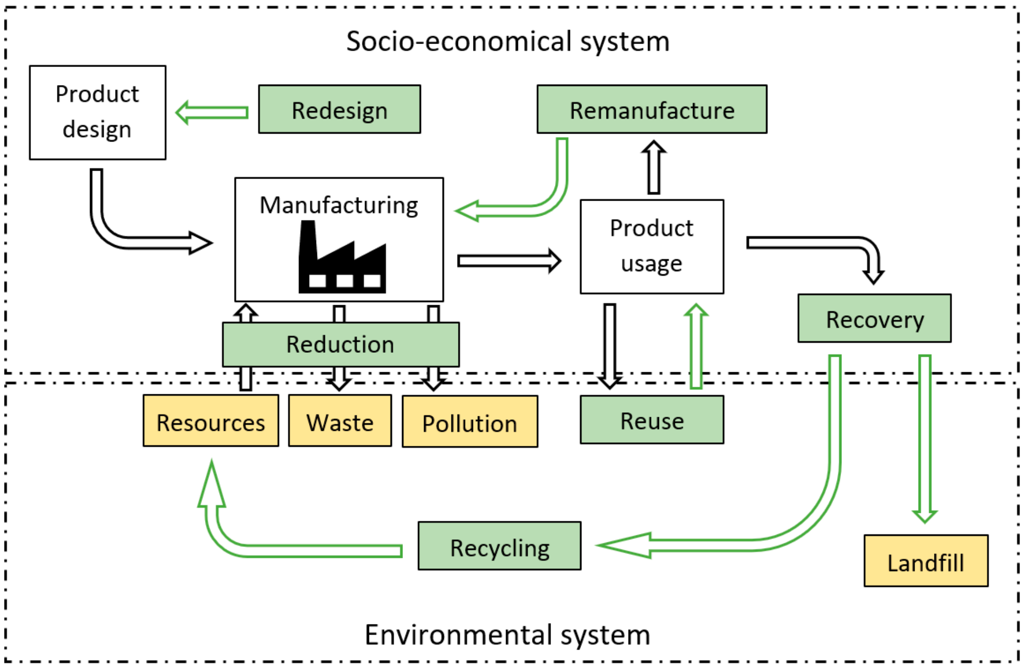

Figure 1. The 6R concept placed in an environmental and socio-economical system.

The concept of designing towards sustainability refers to methodologies which improve the design process, materials, and supply chains in order to make a sustainable product. More sustainable products can help companies move towards sustainable manufacturing that aims to produce high-quality products using fewer resources or more sustainable resources [13]. Sustainable manufacturing is possible when a company considers the entire product life cycle and it is not limited only to product design, manufacturing, and product usage [14]. In recent years, sustainable manufacturing has often been linked with the closed-loop and circular economy concepts [10].

Eco-innovating product designs tend to involve both better functionalities of a new product and ecological soundness [15]. For example, the development of digital cameras has significantly reduced the use of traditional film and other related devices and materials, including highly toxic, nonbiodegradable, and hazardous chemicals. Moreover, designing sustainable products enhances a company's image regarding its efforts towards innovativeness and reduction of negative environmental impacts. In incorporating an eco-product or eco-innovation concept into the new product development process, companies adjust their strategy towards a proactive mindset and long-term sustainability, which is often an evolution away from an earlier, reactive orientation, in which changes result from environmental regulations and stakeholder pressures [16]. A methodology for identifying relationships between eco-innovation and product success is presented in [17]. It is noteworthy that product sustainability is often assessed by consumers through a product's appearance and its eco-design, including eco-labeling, green color, etc. [18]. Issues related to product remanufacturing or recovery are mostly neglected by consumers during their buying choices. The eco-design concept incorporates environmental issues into new product development alongside traditional issues related to profit, functionality, quality, ergonomics, image, and aesthetics. Generally, eco-design should be performed according to the following objectives: reducing the consumption of resources and negative environmental impacts and increasing product value [19].

Sustainable manufacturing refers to the creation of products minimizing negative environmental impacts, the consumption of energy and natural resources, and being economically viable and safe for employees, communities, and consumers [10]. Incorporating sustainability into manufacturing requires a holistic view from the perspective not only of the product and production processes, but also the whole supply chain and multiple product life cycles [20]. As a result, models and optimization techniques should be adjusted at the product, process, and system levels. At the product level, the 6R concept has replaced the earlier 3R concept (reduce, reuse, recycle) facilitating drift from the single life-cycle to multiple life-cycle paradigm. At the process level, manufacturing companies try to achieve technological improvements in order to reduce consumption of energy, materials, toxic wastes, etc., and to improve product quality, and consequently, extending its life cycle. At the system level, all product life cycle stages (pre-manufacturing, manufacturing, use, and post-use) are considered in the context of the whole supply chain and multiple life-cycles.

Sustainable product development and eco-friendly products are designed by R&D specialists who should be supported in this complicated process and who should refer to the entire product's life cycle and consider the reduction of resource consumption, negative environmental impacts, and the increase of a product's value. If a new product is not based on a wholly novel design, there is the possibility of using data-driven approaches for improving sustainable product development.

2.2. Data-Driven Approaches for Sustainable Product Development

Data-driven approaches are commonly used in sustainable development, including sustainable supply chain management [21–24], e-mobility [25], manufacturing [26–29], and product design [30–32]. A data analytics framework for sustainability performance can be considered in four areas: data acquisition, storage and preprocessing, data mining, and data application services [33]. The first area, data acquisition, is related to company databases, such as computer-aided design and engineering systems-supported product design. Data storage and preprocessing refer to retrieving data from databases, data cleaning, integration, reduction, and transformation to a form recognized by a data-mining technique. Data-mining models are related to a considered problem (e.g., regression, association, classification, and clustering), and determined using specific techniques (e.g., artificial neural networks, genetic algorithms, and support vector machines). The last area, data application services, is dedicated to supporting users when solving a specific problem, such as those related to design optimization, processing parameters, quality improvement, and energy optimization.

The improvement of sustainability performance requires metrics and evaluation methods. One method dedicated to evaluating the potential environmental impacts of a product is life cycle assessment (LCA). The LCA concept has evolved into life cycle sustainability assessment, incorporating additional economic and social aspects. These three aspects (also called dimensions or pillars) of sustainability are known as the triple bottom line and refer to economic growth, social well-being, and environmental stewardship [10,34,35]. Indicators for economic growth can include profits, costs, and investments. Social well-being can be considered from the perspective of employees, customers, and community development, and be measured in terms of health, safety, and satisfaction. In turn, environmental stewardship can be measured by indicators such as water use, consumables reuse ratio, scrap recycled ratio, greenhouse gases, other pollutants, energy and materials use and their efficiency, land use, and natural habitat conservation [34]. The economic dimension of sustainability can also be expanded to encompass product development costs and time and regionalized and personalized products, as well as performance evaluation including product costs, lead time, and product quality [36].

Life cycle sustainability assessment helps evaluate the sustainability performance of a new product at the product design stage. As a result, not only part dimensions, geometries, and material properties can be included in the design optimization process, but variables related to an environmental aspect (e.g., material and energy consumption) can also be incorporated into this process [37]. A data-driven approach dedicated to evaluating sustainable product development should enable the selection and classification of evaluation indicators. One of the most commonly used classifications is the division of indicators between two groups [37–40]: the final evaluation (e.g., environment and economy) and the process evaluation (e.g., material and energy consumption, repair rate, recyclability, raw material cost, production cost, and service cost). In turn, the selection of evaluation indicators is strictly related to a considered problem.

Data-driven approaches for product sustainability assessment use often methodologies related to quality function deployment and multi-attribute utility theory [41], analytical hierarchy process [42–44], fuzzy analytical hierarchy process [9], analytical network process [45], case-based reasoning [46], and multi-criteria decision analysis [47–49]. A comprehensive literature review of data-driven approaches in achieving sustainable development goals in developed, emerging, and developing countries is presented in [50].

Data-driven approaches for product sustainability development are dedicated not only to evaluating the sustainability performance of a new product but also to identifying patterns among data. These patterns can be used to make predictions about sustainability performance and simulations for improving this performance. In this second case, simulations can provide prerequisites (in the form of values of variables within an assumed model) for obtaining the desired level of sustainability performance. A simulation model is then built to these specifications based on a reverse approach.

2.3. A Reverse Approach for Supporting Sustainable Product Development

A reverse approach often appears in literature devoted to product sustainability in the context of reverse logistics and reverse engineering. Reverse logistics activities derive from environmental issues, including legal regulations, ecological awareness, and perception of corporate social responsibility. Reverse logistics focuses mainly on the backward flow of materials, packaging, and finished goods, from the point of consumption to the point of recycling, reuse, remanufacture, repair, refurbishing, or proper disposal of these materials and goods [51]. A review of reverse logistics definitions, trends, and new challenges are presented in [52]. Systematic literature reviews, devoted methods and criteria dedicated to assessing reverse logistics are presented in [53–57]. Reverse logistics in the context of remanufacturing, Industry 4.0, and closed-loop network structures are considered in [58–62]. Finally, a reference model and related methodology of reverse logistics for improving sustainability in the supply chain is proposed in [63].

Reverse engineering aims to extract valuable information from an existing object to create a model. Reverse engineering is closely related to 3D scanning, the use of CAD software for modeling an object, and 3D printing for creating prototypes of a product [64–66]. It can also be supported by CAE software to carry out simulations for validating and optimizing kinematics, finite elements, and mechanical analysis. Reverse engineering allows companies to reduce the time spent creating 3D CAD models [67].

A reverse approach can also be considered in the context of obtaining the target cost. The target cost process enables companies to determine the product cost, by which they can achieve the required functionality, quality, and profit margin for a new product. The traditional target cost process has been extended towards the total cost management approach and target life cycle cost, incorporating aspects related to information systems, strategic planning, and sustainability [68]. Target life cycle cost is assessed at the product design stage because the product features, and consequently related costs, can then be fairly easily modified. The reverse approach regarding reducing the total cost at the product design stage is presented in [6]. It is noteworthy that prediction of costs related to the entire product life cycle is a pivotal element at the product design stage to enhance the probability of developing a successful product in the context of its sustainability performance.

The reverse approach, when dedicated to identifying opportunities for changing product design as a means of improving sustainability performance, requires specifying a model related to a specific problem and its solution through simulations. The above-mentioned model is elaborated on to produce simulations and it consists of variables, their domains, and constraints. Simulations are commonly applied in companies in many areas of its activity, such as in improving product reliability [69,70], order management [71], manufacturing processes [72,73], and business models in general [74]. Simulations of sustainability performance are preceded by the selection of sustainability criteria, sustainability indicators, and calculation approaches [75,76].

The reverse approach enables R&D specialists to obtain information related to possible changes in the design process as a means of achieving the desired sustainability performance.

3. The Proposed Method for Improving Sustainability Performance

One proposed method is dedicated to supporting the R&D department in improving product sustainability at the product design stage. The presented method enables R&D specialists to become familiar with opportunities for changes through which product sustainability will be improved at the manufacturing and product usage stages. These changes can refer to the reduction of material and energy consumption, resulting in improved environmental and economic aspects of product sustainability. Reducing energy consumption is particularly significant in the case of energy-intensive household appliances, such as dishwashers, water heaters, refrigerators, washing machines, washer–dryers, ovens, air conditioners, irons, etc. These types of products should be intentionally designed for longer and more intensive usage by the customer, thereby improving their sustainability.

The presented method is intended for new products that do not use completely original designs but for products that are modifications of past or existing products. As a result, the methodology of research presented in this study can be based on a data-driven approach that uses company databases. The methodology used in this study can be employed in the following areas:

1. Data acquisition
2. Predictive analytics
3. Simulations

Data acquisition aims to use data related to product design, manufacturing, and product usage. The design process is supported by computer-aided design (CAD) and computer-aided engineering (CAE) software. The production process is often supported in manufacturing companies by systems such as enterprise resource planning (ERP) and computer-aided manufacturing (CAM). In turn, data related to customer complaints, warranty costs, and market feedback on advertising campaigns are registered in customer relationship-management (CRM) systems. Company databases can also contain communications related to expectations from potential customers about the functionality of a new product and technological limitations reported by R&D specialists. In accordance with a specific problem, variables and constraints are retrieved from company databases to determine relationships, further predict sustainability performance and identify improvement opportunities in product design as a means of increasing sustainability performance. Relationships between input variables and an output variable (such as sustainability performance) are determined using data acquired from company databases. Data selection should embrace the data related to previous products that are most similar to a new product. Simulations are carried out using constraints programming that requires specifying the considered problem in terms of a constraint satisfaction problem. Figure 2 presents a framework for the proposed method.

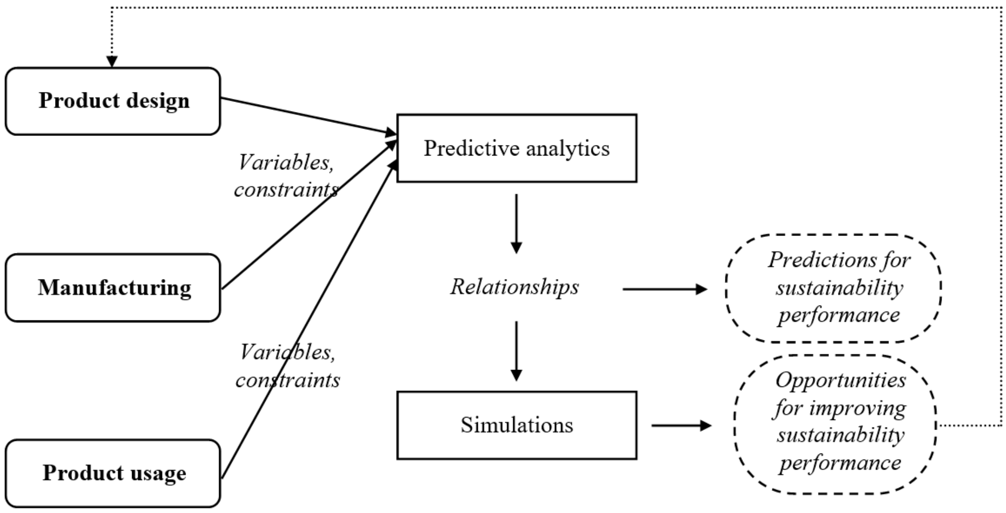

Figure 2. A framework for the proposed method.

The dotted line in Figure 2 indicates information addressed to R&D specialists to support them in designing a new product as a means of increasing its sustainability at the manufacturing and usage stages. The details related to the two main parts of the proposed method, namely predictive analytics and simulations, are described below.

3.1. Predictive Analytics for Sustainability Performance

Sustainability performance can be evaluated within the environmental, economic, and societal qualities of a product through the product's complete life cycle. One factor related to sustainability performance is material and energy consumption, which is considered in this study. Material consumption is mainly considered in manufacturing, but it also affects the use and post-use stages of the product's life cycle. For example, the usage of high-quality materials can result in reducing the number of defective products, thus extending the product's life cycle and consequently improving product sustainability. In turn, energy consumption is considered in both the manufacturing and product usage stages. Energy consumption depends on the type of household appliance, its features, and its functionalities. For example, the energy consumption of a dishwasher is related to wash time, temperature and volume of water, and number of wash cycles and dish-care options. The selection of product parameters provides input variables for parametric modelling to determine relationships and ultimately predict and simulate sustainability performance.

Parametric modelling can be performed using many approaches from regression analysis to computational intelligence. Regression analysis provides linear or nonlinear models for predicting or inferring causal relationships. Computational intelligence is based on nature-inspired methodologies that are dedicated to solving complex real-world problems for which traditional modelling is limited. Among these methodologies can be found fuzzy logic systems, artificial neural networks, and evolutionary algorithms. There are also hybrid-built systems which combine the advantages of individual techniques, such as fuzzy neural systems [77]. The application of regression analysis includes advantages such as ease of implementation and lower computational power in comparison with computational intelligence, particularly in the aspect of complex nonlinear patterns. Regression analysis finds a functional relationship (model or equation) between dependent and independent variables [78].

In this study, both linear and nonlinear regression are used to determine parametric models. Formula (1) refers to multiple linear regression, whereas (2) indicates polynomial regression.

$$y = \alpha_0 + \sum_{i=1}^{n} \alpha_i X_i \tag{1}$$

$$y = \alpha_0 + \sum_{i=1}^{n} \alpha_i X_i + \sum_{i=1}^{n} \beta_i X_i^2 \tag{2}$$

where y is the predicted value of sustainability performance, α_0 is called the initial value, α_i refers to regression coefficients, and X_i is related to n independent variables.

The predictive quality of the above parametric models is measured using the mean absolute percentage error (MAPE).

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

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

The selection of input variables depends on the type of a product, requiring consideration of its significant impact on an output variable (e.g., the number of defective products and energy consumption). Furthermore, input variables should refer to items that can be controlled by management in order to increase the sustainability performance of a new product. An example of an input variable can be the number of prototype tests or the quality of materials used in the production process. The dataset is divided into the training and testing sets to verify prediction quality. Moreover, experiments are conducted for *k*-fold cross-validation and the results are presented as the average of *k*-folds. Cross-validation is a resampling method in which different subsets of data are used to train and test a parametric model within *k* iterations. Sustainability performance is predicted with the use of a model that obtained the lowest MAPE in the testing set.

The determined relationships are used in two fields: predictions and simulations for improving sustainability performance. The parametric models used for prediction require specifying the values of input variables to evaluate the sustainability performance of a new product. These values can be retrieved from company databases related to information systems, such as CAD, CAE, ERP, CAM, and CRM. Company databases include data regarding previous products, their specifications (dimensions, components, and materials used), and problems encountered during design, manufacture, and after-sales service. The values of input variables derive from the most similar previous product that is part of the same product line as a new product. The most similar previous product can be chosen using a similarity analysis that can include a few product features such as the number of components, the number of product functionalities, time and materials used in the manufacturing processes, etc. [6]. The second usage of the determined relationships is to carry out simulations as a means of identifying opportunities for improving sustainability performance.

3.2. Simulations for Improving Product Sustainability

Simulations aim to identify opportunities to improve sustainability performance through changes at the product design stage. In this study, the decision problem within a simulation environment is formulated according to a constraint satisfaction problem (CSP). The CSP is specified in the form of the following triplet:

$$(V, D, C) \tag{4}$$

where

V is a set of n variables $\{V_1, V_2, \ldots, V_n\}$;
D is a set of n discrete domains $\{D_1, D_2, \ldots, D_n\}$ related to variables V;

C is a set of m constraints $\{C_1, C_2, \ldots, C_m\}$.

The CSP can be described as a finite and discrete domain of values that is associated with each variable, whereas a constraint is specified as a relationship within a subset of the set of variables. The description of a decision problem enables the CSP to effectively find a solution, if there is one. The solution of the constraint satisfaction problem resolves in a state in which all constraints are satisfied. For this purpose, learning mechanisms based on constraint propagation prune the search space [79]. Constraint satisfaction modelling can be seen as a paradigm which improves algorithmic techniques dedicated to solving real-life problems [80].

The problem of improving the sustainability performance of a new product through incorporating changes in a product during design can be specified as the constraint satisfaction problem. The number of solutions of the constraint satisfaction problem reflects possible changes in a new product and it depends on the number of involved variables, related domains, and constraints that can link variables. The constraints can be related to limitations referring to the technological process (e.g., the minimal density of materials), scarce resources (e.g., the budget for developing new products), and relationships described in the form of parametric models.

Describing the problem specification in terms of the constraint satisfaction problem enables R&D specialists to receive answers to questions related to predictions and simulations, respectively, such as:

- What number of defective products is predicted during manufacture and what will energy consumption be during product usage?
- Is there a possibility of incorporating changes in product design to improve sustainability performance and if yes, what changes are possible?

In this study, the constraint satisfaction problem is solved using a constraint programming (CP) technique that involves constraint propagation and search algorithms. It is relatively simple to find a solution to a constraint satisfaction problem after constraint propagation or to show that a CSP does not have a solution [81]. Constraint propagation can repeatedly reduce domains and/or constraints during its performance. Consequently, CP reduces a constraint satisfaction problem to an equivalent form that satisfies a notion of local consistency [82]. The CP technique is particularly effective compared with an exhaustive search that finds a solution if one exists, but its performance is proportional to the number of possible solutions. Thus, an exhaustive search tends to increase very quickly according to the size of the problem, which limits its applications in many practical problems [80].

4. An Illustrative Example

An example of the proposed approach consists of two subsections regarding two stages of the product life cycle: manufacturing and product usage, respectively. Each subsection presents the model's specifications, identification of relationships, and its twofold usage in predicting output variables and in conducting simulations for improving product sustainability. Moreover, this example aims to illustrate the use of the proposed method to identify possible changes in different stages of the product life cycle, changes that can be implemented at the product design stage. The presented case study refers to household electronic devices, namely to a product line of dishwashers.

4.1. Improving Product Sustainability in the Manufacturing Stage

4.1.1. Model specification

Improving sustainability performance in the manufacturing stage involves the reduction of material consumption and the number of defective products in the production process. This reduction improves the environmental aspect of product sustainability, also affecting its economic impact. Moreover, the use of recyclable materials can reduce the amount of waste at the post-use stage of the product life cycle. A set of variables for determining relationships in the manufacturing stage is as follows:

V_1—amount of material used per product (in g);
V_2—amount of scrap material in manufacturing processes per product (in cm^3);
V_3—size of parts in the product made from aforementioned material (in cm^3);
V_4—material density (in g/cm^3);
V_5—recyclable materials used per product (in %);
V_6—number of defective products (per 1000 manufactured products);
V_7—unit production cost (in EUR);
V_8—cost of defective products (in EUR);
V_9—material cost per product (in EUR);
V_{10}—labor cost per product (in EUR);
V_{11}—energy cost of manufacturing the product (in EUR);
V_{12}—overhead cost per product (in EUR).

The amount of material needed to manufacture a product is calculated according to the following formula:

$$V_1 = (V_2 + V_3) \cdot V_4 \tag{5}$$

In turn, the formula to calculate the number of defective products is as follows:

$$V_6 = f(V_3, V_4, V_5) \tag{6}$$

The cost of defective products related to each 1000 manufactured products is calculated according to the following formula:

$$V_8 = V_6 \cdot V_7 \tag{7}$$

In turn, the unit production cost is determined as follows:

$$V_7 = aV_9 + bV_{10} + cV_{11} + dV_{12} \tag{8}$$

The overhead cost per product (V_{12}) refers to costs that are not directly related to a manufactured product. This cost includes the total cost of advertising, after-sales service, administrative expenses, rent, utilities, etc., which is divided between all manufactured products. The values of variables from V_2 to V_5 and from V_9 to V_{12} are determined using an analogical approach, by identifying the most similar previous product to a new product. The identification of the most similar product can be based on criteria such as product size, weight, features (e.g., stainless steel interior or integrated control panel), the number of wash cycles, and dish care options. An analogical approach to cost estimation is based on product performance in the past. In addition, the estimated cost of a new product should be adjusted for inflation. Coefficients a, b, c, and d in Formula (8) refer to the increasing cost of material, labor, energy, and overhead, respectively. Moreover, coefficient d refers to per-unit fixed costs that can increase if demand decreases due to the increase of product price. The relationship (6) is identified using parametric modeling that is presented below.

4.1.2. Predictive Analytics

The dataset includes 18 previous products that are part of the same product line as a new product. The data were divided into training and testing sets in order to assess the quality of a prediction model. The training set consists of 14 cases whereas the testing set consists of 4 cases. These cases refer to past and existing products which are similar to a new product in type (built-in dishwashers), size (24 inches wide by 24 inches deep by 35 inches high), features (a maximum sound level of 45 dBA), and functionality (the same number of wash cycles). The experiments were performed using five-fold cross-validation and the results were calculated as the average of these iterations. The quality of a prediction model was assessed with the use of the mean absolute percentage errors (MAPEs).

The relationship (6) was identified using parametric models based on the multiple linear (ML) and nonlinear (NL) polynomial regression models. The results of the above-mentioned models were compared to the average (AV) of an output variable, namely the number of defective products. Table 1 presents the comparison of MAPEs for different prediction models in the context of the training set, testing set, and the mean MAPEs for these sets.

Table 1. The comparison of MAPEs for prediction models in the manufacturing stage (in %).

Prediction Model	Training Set	Testing Set	Mean
ML	15.61	17.82	16.72
NL	12.90	15.03	13.97
AV	23.53	27.48	25.51

The comparison of MAPEs presented in Table 1 indicates that prediction models using linear and nonlinear regression outperform the prediction quality for the average of the number of defective products. The fewest MAPEs in the training and testing sets were generated by the nonlinear regression model, which was used to predict the number of defective products for a new product. Using the following values of input variables: $V_3 = 320$, $V_4 = 7.5$, $V_5 = 51$, the number of defective products is predicted at 24 units per 1000 manufactured products.

4.1.3. Simulations for Improving Product Sustainability

Simulations were carried out with the use of constraint programming, in which the specification of variables, their domains, and constraints are needed. Constraints refer to accessible resources as well as the above-presented relationships (5)–(8). Simulations aim to identify opportunities (if there are any) for reducing the number of defective products through possible changes in material density (V_4) and quantity of recyclable materials used per product (V_5). The identified relationship (6) indicates that increasing material density results in improved product quality while simultaneously reducing the number of defective products. As a result, fewer defective products reduce material and energy consumption and related costs in the manufacturing stage. Moreover, an increase in the proportion of recyclable materials in the product results in a slight increase of defective products.

Table 2 illustrates a set of simulations aimed at reducing the number of defective products and the cost of their manufacturing. Simulations were performed using two variables that can be controlled by the company during the production process: material density and ratio of recyclable to non-recyclable materials. The relationship (6) determines the impact of these variables on the number of defective products. For performing simulations, the following domains of the above-mentioned variables were specified: $D_4 = \{7.5, \ldots, 8.4\}$, $D_5 = \{51, \ldots, 60\}$.

Table 2. Simulations of changes affecting defective products and material consumption.

Controllable Variables	Number of Defective Products	Cost of Defective Products	Material Cost	Unit Production Cost
$V_4 = 7.5$, $V_5 = 51$	24	6423	165.1	267.6
...	...	...	...	...
$V_4 = 7.5$, $V_5 = 60$	25	6690	165.3	271.0
...	...	...	...	...
$V_4 = 7.6$, $V_5 = 51$	24	6423	167.4	270.2
...	...	...	...	...
$V_4 = 7.6$, $V_5 = 60$	25	6690	167.6	273.5
...	...	...	...	...
$V_4 = 8.4$, $V_5 = 51$	22	5888	185.6	287.4
...	...	...	...	...
$V_4 = 8.4$, $V_5 = 60$	23	6155	185.8	290.8

The results presented in Table 2 indicate that the change in material density of steel racks from 7.5 to 8.4 g/cm^3 reduces the number of defective products (from 24 to 22) and consequently their cost related to material and energy consumption as well as labor during the production process. On the other hand, the material cost and unit production cost are greater after increasing material density and the proportion of recyclable materials. The above-presented simulations can be expanded using a reverse approach and obtaining the answer to a question about the conditions under which product sustainability is the highest. For example, the minimal number of defective products is produced when material density is 8.4 g/cm^3 and the proportion of recyclable materials is 51%. Moreover, further analysis could be conducted when searching for conditions under which the most desirable cost of defective products is reached. It is noteworthy that defective products affect not only the manufacturing stage but also the use and post-use stages as the number of customer complaints impacts the warranty cost as well as customer satisfaction and loyalty. Therefore, supporting product designers in identifying possible changes for reducing the rate of defective products has particular significance.

4.2. Improving Product Sustainability in the Usage Stage

4.2.1. Model Specification

Improving sustainability performance in this stage refers to the reduction of energy consumption during consumer product usage. Energy reduction affects both the environmental and economic aspects of product sustainability. Economic issues of product sustainability in the presented example refer to the costs related to energy reduction. These are the following variables within model specification:

V_{13}—energy consumption of the single product usage (in kWh);
V_{14}—temperature of heating water (in degrees Celsius);
V_{15}—water usage in the wash cycle (in liters);
V_{16}—time of the wash cycle (in minutes);
V_{17}—the unit price of electricity (in EUR per 1 kWh);
V_{18}—cost of energy consumption (in EUR).

The relationship between energy consumption and product usage is as follows:

$$V_{13} = f(V_{14}, V_{15}, V_{16}) \tag{9}$$

The cost of energy consumption is calculated according to the following formula:

$$V_{18} = V_{13} \cdot V_{17} \tag{10}$$

4.2.2. Predictive Analytics

The values of variables from V_{14} to V_{16} are determined by the R&D specialist during product tests. These values are stored in company databases and can further be used in identifying the relationship (9) using a parametric prediction model. This relationship is determined using the same assumptions related to data and parametric model selection as in the previous subsection. Table 3 presents the comparison of MAPEs for different prediction models for the training and testing set and as the mean of the MAPEs for these sets.

Table 3. The comparison of MAPEs for prediction models in the product usage stage (in %).

Prediction Model	Training Set	Testing Set	Mean
ML	13.79	16.14	14.97
NL	11.95	14.60	13.28
AV	19.22	21.71	20.47

The results of experiments indicate that the linear and nonlinear prediction models outperform the results for the average of energy consumption for single product usage. The fewest MAPEs were generated by the nonlinear regression model, which was further used in predicting the energy consumption of the single usage of a new product. Assuming the following values of input variables: V_{14} = 55, V_{15} = 10, V_{16} = 45, the energy consumption of the single product usage is predicted to be 1.8 kWh. The energy cost of the single product usage (V_{18}) reaches 0.45 EUR, assuming the unit price of electricity equals 0.25 EUR per 1 kWh.

4.2.3. Simulations for Improving Product Sustainability

Simulations presented below aim to find opportunities for reducing energy consumption within the product usage stage. Energy consumption was simulated for two input variables: the temperature to which water was heated (V_{14}) and the duration of the wash cycle (V_{16}), assuming the following domains for these variables: $D_{14} = \{50, \ldots, 60\}$ and $D_{16} = \{40, \ldots, 50\}$. Table 4 illustrates changes in energy consumption depending on different values of the above-mentioned input variables.

Table 4. Simulations for energy consumption for the single product usage.

Variables	Energy Consumption (in kWh)	Change of Energy Consumption (in %)
V_{14} = 50, V_{16} = 40	1.62	−9.9
...	...	...
V_{14} = 50, V_{16} = 50	1.78	−1.3
...	...	...
V_{14} = 51, V_{16} = 40	1.64	−8.8
...	...	...
V_{14} = 51, V_{16} = 50	1.79	−0.1
...	...	...
V_{14} = 55, V_{16} = 45	1.80	0
...	...	...
V_{14} = 60, V_{16} = 40	1.82	1.3
...	...	...
V_{14} = 60, V_{16} = 50	1.98	9.9

The results of simulations indicate that the unit increment related to water has a stronger impact on energy consumption than the unit increment of the duration of the wash cycle. The decrease of the water temperature and the duration of the wash cycle by 5 units can result in reducing energy consumption by approximately 10%. This information can support R&D specialists in designing products according to environmental and economic requirements. The presented analysis can be developed towards searching for parameters of product usage in which the desired level of energy consumption is achieved. For instance, if energy consumption should be reduced by 12% (below 1.58 kWh), then the first possible solution uses the following values for input variables: V_{14} = 49, V_{16} = 38. Another direction of simulations can refer, for example, to using new pumps that increase water pressure, improving energy consumption.

It is noteworthy that simulations can generate a very large number of possible solutions extending the time needed to find all solutions. Constraint propagation can significantly reduce computational time in comparison to an exhaustive search and consequently it can be useful to search a large variety of possible solutions [80]. The advantage of using constraint programming techniques in the context of time efficiency is illustrated through experimental results presented in Table 5.

As mentioned above, a number of possible solutions to the considered problem is related to the number of decision variables, their domains, constraints, and the granularity chosen for variables. Initially, the granularity of V_{14} is measured in degrees Celsius, the granularity of V_{15} in liters, and the granularity of V_{16} in minutes. Decreasing the granularity for variables V_{15} to one quarter-liter and V_{16} to a half-minute boosts the search space and the number of possible solutions. Table 5 shows the experimental results of two cases of searching solutions for different strategies of constraint propagation. The first case is related to the following specification: D_{14} = {50, ... , 60}, D_{15} = {8, ... , 12}, and D_{16} = {40, ... , 50}. In turn, the second case includes the extension of domains for D_{15} and D_{16}: D_{14} = {50, ... , 60}, D_{15} = {8.0, 8.25, ... , 12.0}, and D_{16} = {40.0, 40.5, ... , 50.0}. The exhaustive search (ES) is compared to various strategies implemented in constraint programming in the factors of the number of nodes checked and time needed for finding possible solutions. The calculations have been performed in the following hardware: IntelCore(tm) i5 4 GHz, RAM 8 GB.

Table 5. Time efficiency for different search strategies.

Case	Search Strategy	Nodes Checked	Time [s]
1	ES	605	0.23
	CP Naïve	121	0.14
	CP First-fail	121	0.12
	CP Split	121	0.12
2	ES	3927	1.78
	CP Naïve	561	0.86
	CP First-fail	561	0.53
	CP Split	561	0.44

Experimental results illustrate the advantage of using constraint programming for reducing computational time. This is particularly significant for the large search areas. Consequently, constraint programming improves the interactive properties of a decision support system dedicated to the considered problem. It is noteworthy that the user of the decision support system can receive all possible solutions, a few, or only one according to criteria regarding sustainability performance such as the maximal reduction of energy consumption.

5. Conclusions

The presented approach has been developed with the intention of supporting R&D departments in searching for improvement opportunities in product design, aiming at increasing sustainability performance of a new product. These improvement opportunities may involve increasing the quality of used materials and consequently reducing the number of defective products in manufacturing and extending the product usage stage. Improving product sustainability is also related to energy reduction during product usage. This reduction is particularly important in the context of household appliances which are often energy-intensive products intended for long-term usage.

The main contribution of this research is the use of a constraint satisfaction problem for generating a simulation model for obtaining all possible improvement opportunities, if there are any, within specified variables, their domains, and constraints. The problem specification in terms of a CSP enables the use of constraint programming and as a result, a time-effective reduction of the search space, which ensures the interactive properties of a decision support system dedicated to the considered problem. Additionally, the problem formulation in terms of a constraint satisfaction model enables the gradual development of a knowledge base which is the main part of a decision support system, and consists of facts, constraints, and relationships specified as if-then rules. The managerial implications are related to supporting R&D specialists in searching for improvement opportunities of product sustainability, and to supporting top management in improving production effectiveness through reducing the number of defective products.

Constraint satisfaction modeling allows R&D specialists to receive information about all admissible changes in product design in order to improve sustainability performance. These changes can be new and surprising for them, revealing new directions of product modifications. However, the performed simulations can provide the large number of solutions that can exceeds human abilities to result interpretation. This seems to be the main limitation of the proposed approach. Moreover, the presented approach uses company databases, which include specifications of the previous products belonging to the same product line as a new product. Consequently, this approach cannot be used for supporting the design process dedicated to innovation or products belonging to completely new product lines. Additionally, data acquisition only from company databases and data preprocessing required to the effective use of a simulation environment can also be seen as limitations of the proposed approach.

The presented limitations can be an incentive for future research. For example, the large number of solutions can be reduced through increasing granularity of decision variables. Future research will also be necessary to obtaining information from potential consumers about their purchasing preferences, the acceptable price of a new product, its energy consumption, and desirable product functionalities in the context of product sustainability. This information will expand the usability of the proposed approach towards its application for evaluating sustainability performance of innovations or products belonging to the completely new product line. Moreover, further research will include the development of a decision support system dedicated to the considered problem to help the user select the most appropriate data from company databases, the most appropriate parametric model to determine relationships between variables, and reducing the number of solutions according to the user's preferences (e.g., the maximal level of sustainability performance). Another direction of future research will be cost analysis and the reduction of the number of defective products in the case of implementing the Industry 4.0 paradigm, in which waste material derived from manufacturing defective products would also be saved. Moreover, future research will include a more comprehensive cost-benefit analysis in terms of identifying the impacts of increasing material density and reducing defective products on various areas beyond the sustainability perspective.

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