

Article

Decision-Making Model Supporting Eco-Innovation in Energy Production Based on Quality, Cost and Life Cycle Assessment (LCA)

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Abstract: Currently, the development of renewable energy products (RES) encourages the search for innovative solutions that take into account key criteria from the point of view of their sustainable development. Despite efforts in this area, there is a lack of approaches and tools to support this process. Therefore, the aim of the research was to develop a decision-making model supporting eco-innovation in products based on the key criteria of sustainable development: quality (customer satisfaction with use), environmental impact in the life cycle (LCA), and the cost of investment incurred in the product development. The functioning of the model was based on the following factors: (i) obtaining the voice of customers (VoC) and processing it into product criteria as part of the development of alternative production solutions (prototypes), (ii) prospective quality assessment and subsequent life cycle assessment of prototypes, (iii) cost analysis taking into account both quality and environmental criteria, (iv) interpretation of results and search for eco-innovative product solutions. Development decision-making is additionally supported by techniques implemented in the model, e.g., the CRITIC method, the LCA method with Ecoinvent database in OpenLCA, the CEA method, and the morphology method. The model was illustrated and tested for photovoltaic (PV) panels, after which a global sensitivity analysis was performed in Statistica. The test results showed that the main factor that influenced the PV development decisions was the investment cost, followed by quality (customer satisfaction) and then environmental impact in LCA.



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1. Introduction

The use of products, including renewable energy sources (RES) [1], i.e., those whose use is associated with less environmental pollution, often refers to the use of processes with higher efficiency [2]. Therefore, it is important from the point of view of sustainable development of RES to predict their use patterns, including focussing on the impact on the environment, for example, acid rain, ozone depletion, or global warming [3]. It is also essential to search for technologies or methods for eco-innovative product solutions [4], that will meet the challenges of climate, but at the same time that will be satisfactory to customers in terms of quality, including at an affordable price [5,6]. This remains a challenge, as concluded from the review of the literature in the area of sustainable development of RES products.

Among others, Naqvi et al. [7] analysed the possibilities of biofuel production in terms of their sustainable development by using social, economic and environmental practices. It was shown that the factors driving the use of biomass are increasingly attracting the attention of potential stakeholders who are aware of the potential and limitations in practices that support its sustainable development. Similar issues were addressed by Gurkan and Ozgen [8], who analysed the efficiency and quality of pumpkin seed biofuel

in the aviation industry and addressed similar issues. It was confirmed that the offered biofuel can support sustainable development, being important in issues related to the environment and global warming, and increasing customer satisfaction during its use. However, the research conducted by Cao et al. [9] was based on the development of a theoretical model with sustainable development indices, including those related to the environment, economy, and society. Its use allowed us to indicate that the level of the industrial sector is largely dependent on renewable energy sources, and the efficiency in this area can be improved by the sustainable use of RES within the framework of improving technology or limiting resources. In turn, Thanh [10] proposed a model that takes into account multicriteria decision support methods to support decision-makers in the selection and assessment of the efficiency of RES efficiency for the sustainable development of industrial complexes. The integrated methods used in this model were as follows: Spherical Fuzzy Analytic Hierarchy Process (SF-AHP), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). Another example is the study of Sobocińska [11], which analysed the decision-making processes of consumers towards renewable energy compared to other ecological products. The attitudes of consumers toward the ecological products offered within RES by people who had not had contact with them before were also verified. The key attributes encouraging the choice of RES are their price, quality and certification from the manufacturer. In addition, life cycle analysis (LCA) studies have been conducted on the example of renewable energy sources, such as in the study presented by Stoffels [12], where an analysis of the selection of materials was carried out taking into account their environmental impact in the life cycle, as well as technical and economic criteria. The proposed analysis supports the sustainable development of materials and products made from them. Wang et al. [13] presented a methodology combining the Data Envelopment Analysis (DEA) window model, and the Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) was proposed. The offered approach is used to assess the possibilities of countries in terms of their potential to use RES. Various criteria are taken into account, i.e., economic, social, access to resources, environmental, or technological conditions. The results of this method can contribute to sustainable development, including appropriate investments in RES. The aspects of sustainable development of RES were also examined by Majid et al. [14], where the impact of decision-making for their effective use in small and medium enterprises (SMEs) was studied. Ecoefficiency and ecological behaviours, including the innovation policy of enterprises in relation to the use of RES, were examined. The results of this study may be useful in making appropriate decisions in SMEs, including influencing the financial result of the company and thus supporting its sustainable development. On the other hand, Gkeka-Serpetsidaki et al. [15] conducted a review of the literature on the subject, after which they showed that the factors that should be taken into account in analyses, e.g., spatial planning criteria related to social and economic factors, e.g., employment or economic indicators. Legal and ownership criteria are also important, including location and distances from key places. An important problem was raised by Arnaoutakis et al. [16], where the energy distribution was analysed depending on its storage. The key criteria for the analysis were those belonging to different storage technologies. Numerous research works also focused on the topic of energy communities, such as those of Katsaprakakis et al. in [17]. They showed that perhaps energy community models can bring not only greater social but also economic benefits while limiting the negative impact on natural ecosystems. The complex summary of the literature review is shown in Table 1.

Table 1. Summary of the literature review.

Reference	Main Theme	Context
[7,9]	Sustainable development of product considering social, economic, and environmental criteria	Striving for customer satisfaction, reducing negative environmental impact and optimizing costs
[8]	Sustainable development of product considering social and environmental criteria	
[12]	Sustainable development of product considering social, economic, environmental, and technical criteria	
[13]	Sustainable development of product considering social, economic, environmental, technical, and access to resources criteria	
[17]	Energy communities with social, economic and environmental aspects	
[15]	Improving product considering social and economic criteria, and also localization and distance from a key place	Spatial planning
[16]	Analysis of energy distribution depending on its storage	Storage technologies
[11]	Analysis of consumer decision-making towards ecological products and their quality	Consumer decision-making
[14]	Analysis of enterprise decision-making towards eco-efficiency, ecological behaviour, innovation policy	Enterprise decision-making

Based on the literature review, it was shown that analyses were carried out concerning renewable energy products in relation to their sustainable development. For example, economic, environmental, and social criteria were addressed in various ways. However, no coherent approach was developed, including a comprehensive methodology supporting the implementation of eco-innovative product solutions while combining these key criteria of sustainable development. The lack of such studies was determined in the context of designing or improving products to simultaneously meet customer expectations of their use (quality), reduce the negative impact of the product in its life cycle (LCA), and assess the profitability of financial investments (costs). This was considered a research gap that was assumed to be filled within the proposed model.

Therefore, the aim of the research was to develop a model that supports the search for eco-innovative product solutions toward their sustainable development. The model was developed in a general way, so that it could be widely applied to various types of products, outlined as follows: (1) Inspiration and selection of the research subject, (2) Obtaining the voice of customers regarding product attributes, (3) Identification of technical criteria, (4) Development of product prototypes, (5) Prospective assessment of the quality of product prototypes, (6) Prospective assessment of the life cycle of prototypes (LCA), (7) Cost-effectiveness analysis (CEA), (8) Interpretation of results and setting the direction of improvement actions. A test of the model was carried out for photovoltaic panels, which are considered to be key products of renewable energy sources.

The offered model is dedicated to manufacturing companies, including decision-makers and managers at early stages of product development, and especially in the improvement process. It supports the adoption of eco-innovative product solutions that will simultaneously meet the expected quality, environmental, and cost criteria in the best possible way.

The main part of the article is Section 2, which includes a detailed presentation of the model, including the idea, concept, and assumptions of the model, graphical presentation, and characterisation of the model stages, and Section 3 includes an illustration and test of the model on the example of PV.

2. Development of Model

Sustainable product development, taking into account the multidimensional approach to the improvement process, is still a challenge. Therefore, the aim of the research was to develop a model that supports the search for eco-innovative product solutions toward their sustainable development. The concept of the model is based on the mentioned eco-innovations, the result or purpose of which represents noticeable progress towards sustainable development [18,19]. It manifests itself through reducing the negative environmental impact, increasing environmental efficiency, or making a thoughtful use of natural resources. Eco-innovations are associated with the ecological industry and ecoefficiency, including sustainable production and consumption [4,20]. Therefore, the idea of these approaches was a framework for developing the proposed model. The model was created on the basis of three key criteria of sustainable development, which are as follows:

- Quality—understood in this approach as meeting customer expectations about product usability, interpreted as product quality (customer satisfaction with quality criteria that influence usability) [21,22];
- Environmental impact—interpreted as the impact of the product on the environment in the life cycle (LCA), including the environmental burden for the selected impact criterion in the product life cycle (according to the ‘cradle to grave’ approach) [23,24];
- Cost—it is assumed that it is the cost incurred to cover the quality of the prototype, taking into account its environmental impact in the life cycle (LCA), including the cost of investment in the product or the cost of purchasing the final product by the customer [25].

The functioning of the model is based on a multidimensional and multicriteria analysis of the product towards its sustainable development. At the early stage of the product improvement process, including designing eco-innovative solutions, various product prototypes are created. The starting point for creating prototypes is the current product (existing and on sale). Initially, the voice of customer (VoC) [26,27] is acquired in order to determine what is important to customers in the product in the context of its usability. Customer requirements are transformed into technical criteria, as, for example, in the QFD (Quality Functional Development) method [28,29]. After standardising the customer requirements, prototypes are created that focus on the criteria (attributes) expected by the customer. Then, the quality of these prototypes is evaluated using the multicriteria decision support method, that is, CRITIC [30]. As a result, a quality indicator (Q) of the product prototypes is developed. Subsequently, developed prototypes are subjected to a prospective life cycle environmental impact assessment (LCA) [31]. It is proposed to use the ‘cradle to grave’ approach, including the guidelines of the ISO 14040 standard [32]. In this way, an environmental burden indicator is obtained, depending on the selected environmental criterion in the prototype life cycle (LCA). Later, the indicators are aggregated into one coherent quality–environmental indicator (QLCA). The QLCA indicator presents the so-called eco-efficiency of prototypes in the next analysis process, which is cost-effectiveness analysis (CEA) [33]. Then, the cost of investment in a given prototype is taken into account in order to check the profitability of this investment in relation to the offered quality and taking into account the environmental impact of the prototype in the life cycle. Finally, the ICER–QLCA indicator (incremental cost-effectiveness ratio–quality-life cycle assessment) is created, based on which the model results are interpreted, including the selection of the most advantageous prototype from the quality–environment–cost point of view. This process is supported by a matrix of graphical interpretation of results, including morphological analysis. This approach favours the selection of a prototype with the characteristics of eco-innovative product solutions toward sustainable development. The developed model includes eight main stages. Its graphical presentation is shown in Figure 1. The method of model implementation is presented step-by-step, as presented in the later part of the study.

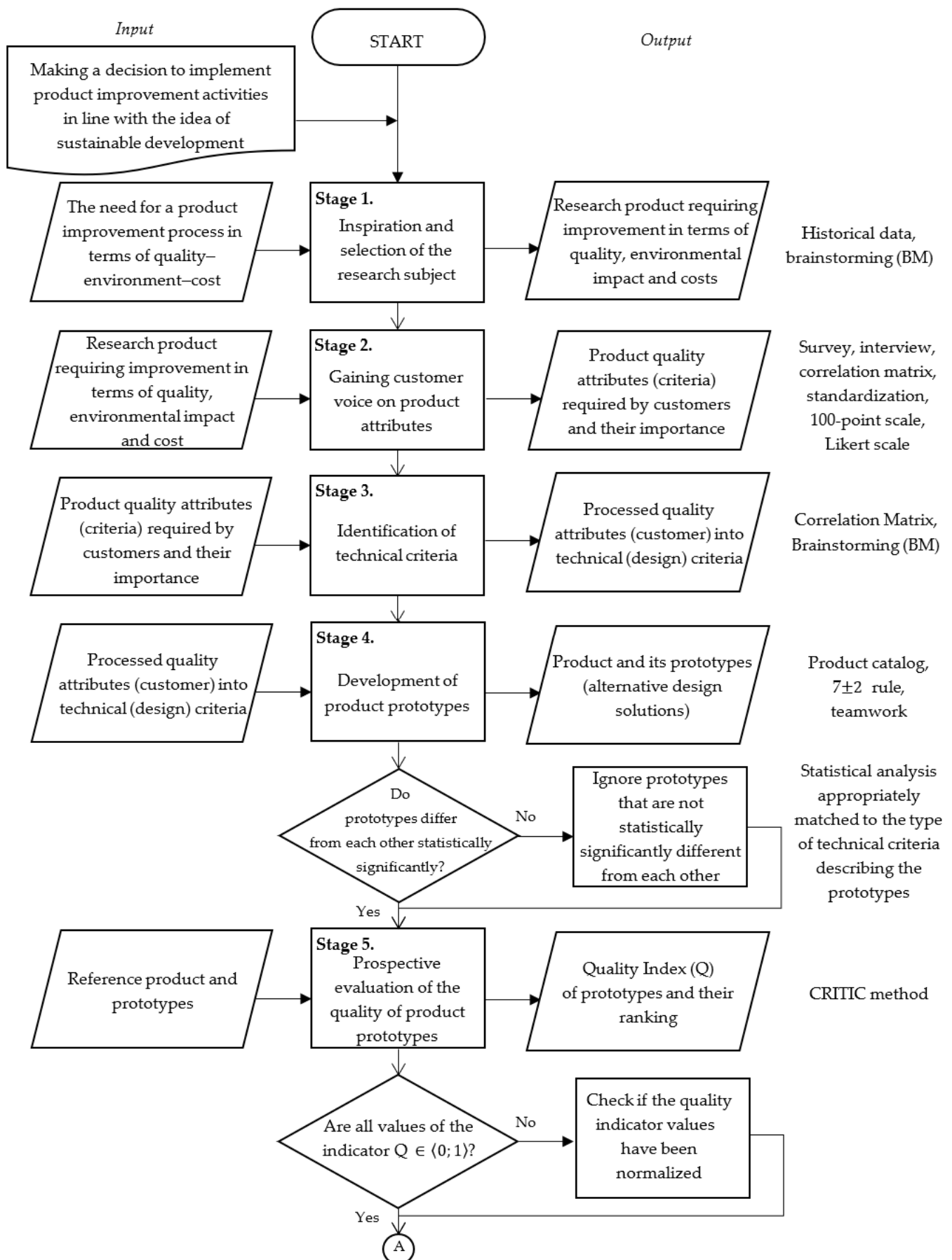


Figure 1. Cont.

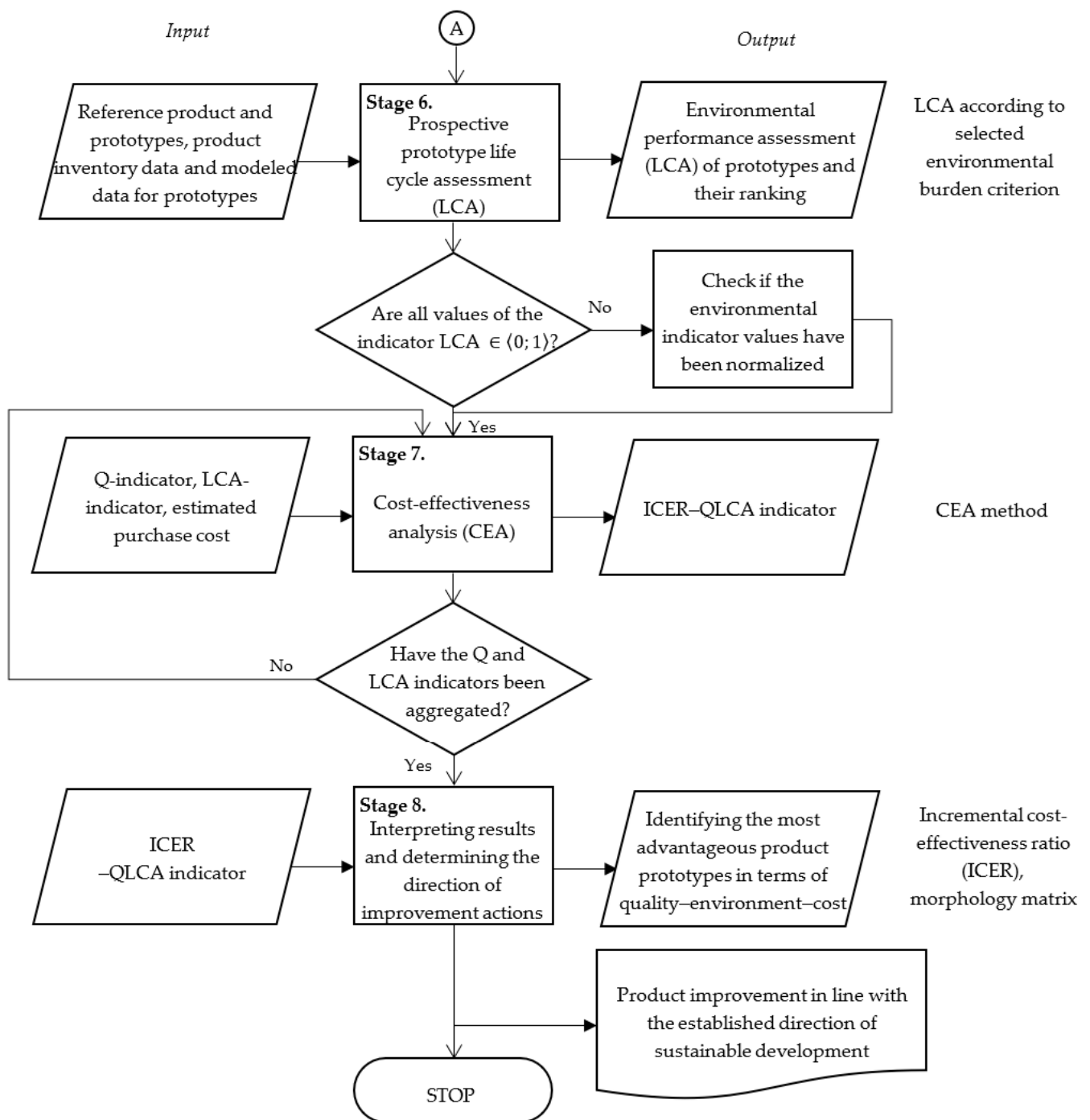


Figure 1. Decision-making model to develop eco-innovation solutions to improve products.

Stage 1. Inspiration and selection of the research subject. The need to use the model may result from the individual needs of the entity using it, e.g., a decision-maker, designer, or manager. The model is dedicated to supporting decisions within the framework of creating new and innovative products, taking into account the key criteria of sustainable development (quality, environment, and cost) [34]. The subject of the research is arbitrary, it may be in the maturity phase or require re-design due to market needs. The idea of the model assumes that these will be products used by customers; hence, they should be known and commonly used by them. Then, it will be possible to obtain their requirements more precisely at the later stages of the model.

Stage 2. Gaining the voice of the customer on product attributes. The product selected for research should be adapted to the expectations of customers; therefore, it is necessary to obtain their requirements at an early stage of its design. Customers from whom expectations are obtained should have general knowledge about the product, including its purpose [35]. It would be good if they used a product of a similar type, then their expectations could be expressed more precisely based on previous experience with the product. Customer voice is obtained as part of surveys or in-depth interviews conducted directly with the customer [36]. The number of customers from whom requirements must be obtained can be determined using the method presented by the authors in [37], or as in [38]. Customers should indicate at least five to ten attributes of the product that, in their opinion, are important from the point of view of product use [39]. These attributes can then be expressed in a general and subjective way. Furthermore, customers should assign weights to these attributes by distributing 100 points between the indicated attributes, where the higher the number of points, the more important the attribute [40].

Since the attributes will be different, it is necessary to standardise them. For this purpose, you can use, for example, a kinship diagram or keyword analysis [41]. It is effective to conduct this analysis among a team of experts, supported by brainstorming. These attributes are often combined into several coherent groups, usually two to four. Since the attributes were important, it is also necessary to arrange the weights of these attributes in accordance with their adopted order. To do this, the weight values assigned by individual customers for a given attribute should be summarised. Later, they can be divided according to the Likert scale into five weight values, where the largest pools of values have a weight of five (the most important attributes), and the smallest pools of values have a weight of one (the least important attributes) [42]. The standardised product attributes indicated by customers and the importance of these attributes for customers are processed in the next stage of the model.

Stage 3. Identification of technical criteria. As part of effective product design, it is necessary to identify the technical criteria of the product, i.e., criteria used by experts (e.g., decision-makers, designers) at the design and production stage. Therefore, technical criteria are usually measurable [43], for example, length, weight, power, and noise. Initially, it is worth identifying technical criteria that will meet the requirements of the customer. This means transforming the product attributes specified by customers into technical criteria necessary to be determined to effectively design the product. For example, a correlation matrix can be used for this purpose, where the column contains attributes specified by customers, and the row contains proposed technical criteria, e.g., in the House of Quality. This process can be supported by a catalogue of similar products or products designed earlier.

Stage 4. Development of product prototypes. It is proposed to develop prototypes that will be considered as alternative production solutions. It is assumed that the number of prototypes will not be less than five but not more than ten, as in the studies, i.e., [39]. Prototypes are created based on the technical criteria of the product, which were selected in an earlier stage of the model. Initially, the product criteria are described according to the current states of these criteria (current product, on sale). Then, its prototypes are developed according to the current state. The prototypes represent a proposal for other solutions to the parameters of technical criteria rather than in the case of the current parameters of these criteria [44,45]. In this way, these can be values above and below the current state of the criterion parameter. Therefore, they are presented by their corresponding value, value range, or description. Since it is assumed that different product prototypes will be created, each criterion should be described by its current state and by at least five different modifications (no more than ten) [39]. Product prototypes should be developed by a properly selected team of experts [46]. The prototypes developed are subjected to quality assessment, as presented in the next stage of the model.

Stage 5. Prospective evaluation of the quality of product prototypes. The developed product prototypes are assessed in terms of quality, i.e., customer satisfaction with the use

of the product. The qualitative assessment is carried out using the CRITIC method, which is a multicriteria decision support method. The choice of this method resulted from its simple procedure, including the possibility of determining the quality indicator based on any criteria [47]. Based on the set of prototypes and the corresponding criteria in the states of modified parameters f_j , the multicriteria problem is presented as (1) [30]:

$$\max\{f_1(a), f_2(a), \dots, f_m(a) / a \in A\} \quad (1)$$

where: a —parameters of technical criteria of prototypes.

For each criterion for a multicriteria problem, a mapping of the membership function x_j concerning the value f_j from the interval $[0, 1]$ is defined. Then, the transformation is based on the concept of ideal and anti-ideal. The base values should be made dependent on the weights of the criteria in the form of their product, which are subsequently presented by the values $x = j$. The value below represents the degree to which the alternative is close to the ideal, i.e., it is the best solution furthest from the anti-ideal value. Ideal and anti-ideal values occur for each alternative (prototype), as shown in Formula (2) [48]:

$$x_{aj} = \frac{f_j(a) - f_j^*}{f_j^* - f_j^-} \quad (2)$$

where: f_j^* —anti-ideal value, f_j^- —ideal value, a —criterion parameter value, $j = 1, 2, \dots, n$.

Consequently, the initial matrix (comprising product prototypes according to technical criteria and their weights) is transformed into a matrix of absolute scores, which have general elements x_{ij} . Then, by analysing the j -th criteria, a vector x is generated, which denotes the scores for all the alternatives considered (3) [30]:

$$x_j = (x_j(1), x_j(2), \dots, x_j(n)) \quad (3)$$

Each vector x_j is characterised by a standard deviation, which in percentage terms determines the contrast intensity of the corresponding prototype. Therefore, the standard deviation x_j is a measure of the value of the criterion obtained in the decision-making process. Instead, when there are divergent results (e.g., entropy or variance), it can be used instead of the standard deviation. Next, a symmetric matrix is developed which has so-called generic elements, which are the linear correlation coefficient between the vectors obtained earlier. The more inconsistent the results of the alternatives in the individual criteria, the lower the value of r_{jk} , which shows the measure of the conflict created by the criteria in the case of the remaining decision criteria (4) [30,48]:

$$\sum_{k=1}^m (1 - r_{jk}) \quad (4)$$

where: r —measure of conflict between prototype criteria, $j = 1, 2, \dots, n$.

Instead, one can calculate the Spearman rank correlation coefficient to obtain a more general measure of the relationship that connects the rank orders of the vectors. Next, a measure is performed quantifying the multiplicative aggregation pattern, i.e., (5) [30]:

$$O_j = \sigma_j \sum_{k=1}^m (1 - r_{jk}) \quad (5)$$

where: O —quantifying measure, σ —standard deviation, r —measure of conflict between prototype criteria, $j = 1, 2, \dots, n$.

The higher the value of O , the greater the amount of information transferred within a given criterion, as well as its relative importance for the decision that makes progress.

These values are then normalized, resulting in the level of quality of the criteria (q) taken into account within a given prototype (6):

$$Q_j = \frac{O_j - \min O_j}{\max O_j - \min O_j} \quad (6)$$

where: O —quantifying measure, Q —quality of prototype, $j = 1, 2, \dots, n$.

Based on the quality index Q , the overall quality of the prototype is determined taking into account customer requirements. The higher the Q index, the more beneficial the prototype is for customers.

Stage 6. Prospective prototype life cycle assessment (LCA). The model includes a prospective life cycle assessment of product prototypes. The life cycle assessment includes the current (reference) product and proposed prototypes within the prospective assessment. LCA is a method for assessing the environmental impact of a product or process, including a system, throughout its entire life cycle [23]. Most often, according to the ‘cradle to grave’ approach, that is, considering the phases of material acquisition and extraction, production, use, and end of life (EoL) [49]. The life cycle assessment is carried out in accordance with the guidelines of the ISO 14040 standard [32], including the assumption that it will include one selected environmental burden criterion. The environmental burden resulting from the life cycle assessment of the reference product is modelled within the prospective assessment of its prototypes. This is carried out by a team of experts [46,50]. This involves a prospective estimate of the environmental burden value of individual inventory data for product prototypes. On this basis, prospective life cycle assessments are carried out according to the selected environmental burden criterion. The environmental load index (EI) is obtained, which is then normalised in its comparison with the quality index, as shown in Formula (7):

$$LCA_j = \frac{\max EI_j - EI_j}{\max EI_j - \min EI_j} \quad (7)$$

where: EI —value of the environmental burden in the life cycle of the product or its prototype, $j = 1, 2, \dots, n$.

The LCA indicator is an indicator of the environmental burden of a product or its prototype in the life cycle according to the assumed environmental burden. The higher its value, the greater the environmental burden.

The life cycle assessment process can be supported by computer programs.

Stage 7. Cost-effectiveness analysis (CEA). The proposed model additionally takes into account the key cost aspect, which is assumed to depend on the quality aspect and the environmental impact in the life cycle. Therefore, the CEA method [51] is used for this purpose, which is to estimate the cost incurred within the quality coverage of the prototype, taking into account its environmental burden in the life cycle (LCA).

The CEA method is commonly used to assess the impact of medical interventions [52], but it is also effective in the analysis of other types of products. CEA consists of the evaluation of the so-called effectiveness, taking into account the costs of this effectiveness [51]. In the offered approach, if the prototype under consideration is less expensive, with relatively high quality and low environmental burden than its alternative, then it is clearly more profitable, that is, dominant [53]. The problem arises when costs, quality, and environmental burden are divergent, and the decision-maker is not sure about the beneficial solution. Then it is proposed to use the decision-making methodology as in CEA [33]. Assuming, following the authors of the study [33], that these situations accompany innovations, the cost-effectiveness analyses are presented according to the cost-effectiveness ratio (ICER). In the developed model, this coefficient is a reference to the quality of prototypes and their environmental impact during the life cycle.

Therefore, initially, the cost (of investment in a given product/prototype) or the costs incurred by the customer when purchasing the product/prototype should be estimated. They should be expressed in the expected currency. Next, within the standardised compari-

son of the cost to quality and environmental indicators, it is necessary to normalise the cost value to uniform units of measurement, that is, (8):

$$C_j = \frac{\max c_j - c_j}{\max c_j - \min c_j} \quad (8)$$

where: c —cost of investment or purchase of the product, j —product or prototype, $j = 1, 2, \dots, n$.

Then, the quality indicator (Q) and the environmental indicator (LCA) are aggregated into one QLCA indicator presenting both the quality of the prototype and its impact on the environment in the life cycle. Next, the profitability of the investment in a given prototype is estimated in relation to the aggregated QLCA indicator, as shown in Formula (9):

$$\begin{cases} QLCA = \frac{Q_j + LCA_j}{2} \\ ICER - QLCA = \frac{C_j - C_{ref}}{QLCA_j - QLCA_{ref}} \end{cases} \quad (9)$$

where: C_j —normalized cost of the j -th prototype, C_{ref} —normalized cost of the reference product, $QLCA_j$ —aggregated quality and environmental indicator of the j -th prototype, $QLCA_{ref}$ —aggregated indicator of the reference product.

In the offered approach, the ICER–QLCA indicator can be interpreted as follows: The smallest negative ICER–QLCA value is the first position in the ranking and the smallest positive ICER–QLCA value is the last position in the ranking. A detailed interpretation of the results and determination of the direction of improvement actions take place in the last stage of the model.

Stage 8. Interpreting the results and determining the direction of improvement actions. According to the results of the proposed concept, the model is interpreted based on the ICER–QLCA indicator. This is an indicator obtained by simultaneous aggregation of the quality indicator (Q), the environmental burden in the life cycle (LCA), and costs (C). According to the assumptions of the model, in accordance with the ICER–QLCA indicator, it is possible to design a product prototype that will have the highest possible quality and a small negative impact on the environment in the life cycle at a relatively low cost.

In order to facilitate the selection of such a prototype, it is initially proposed to develop a ranking of prototypes according to the value of the ICER–QLCA indicator. The prototype that is most advantageous in terms of quality, environment, and costs is the one whose indicator value is the smallest negative ICER–QLCA value. The next in the ranking are those prototypes whose values increase negatively. However, there may also be positive values for the ICER–QLCA indicator. In such a case, the smaller the positive value, the less advantageous the prototype.

However, decisions on the selection of a prototype that simultaneously meet the three decision criteria (quality, environment, cost) are also determined by the individual capabilities and resources of the company. Therefore, it may be difficult to clearly indicate the most appropriate production solution. For this purpose, the results of the ICER–QLCA indicator act as a linear function of the QLCA and ICER indicators. Following the authors of [33], it is assumed that a prototype is profitable in terms of quality–environment–cost when (10):

$$\frac{C}{QLCA} < T \quad (10)$$

where: C —normalized prototype cost, $QLCA$ —quality–environmental indicator of the prototype, T —profitability threshold (interpreted, for example, as the highest positive aggregate value of the QLCA indicator).

Therefore, it is possible to transform this approach into the following assumption (11) [33]:

$$T \times QLCA - C < 0 \quad (11)$$

For notation, please see Formula (10).

As reported by [33], the values interpreted from Equation (11) can represent the amount that the manufacturer is willing to set and the customer is willing to pay to increase the quality of the offered products, while limiting their negative environmental impact in the life cycle, while reducing the increase in costs that may accompany it. In this way, the decision analysis can be presented as a linear function (Figure 2), which facilitates the manipulation of results according to the preferences of the decision-maker (expert), including their interpretation when considering individual production solutions.

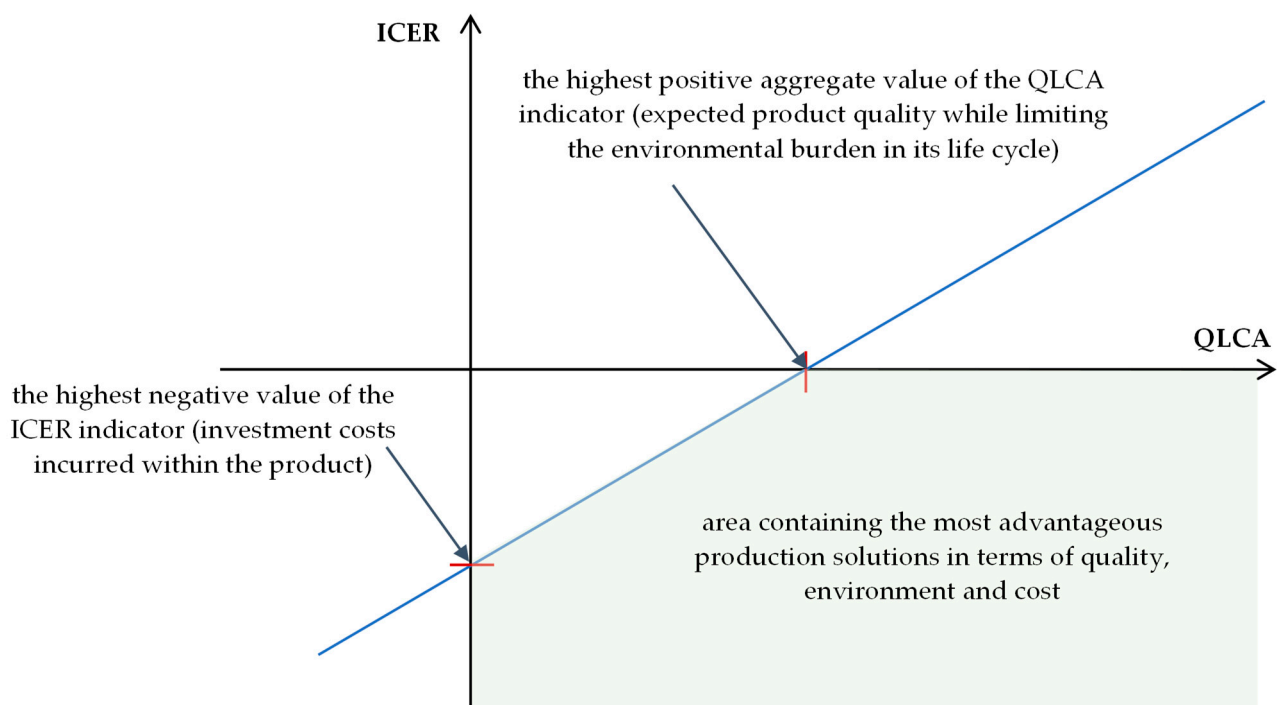


Figure 2. Graphical interpretation of the ICER–QLCA indicator. Own study based on [33].

The area containing the most advantageous production solutions (prototypes) is one in which there are prototypes with a relatively high level of quality and limited negative environmental impact in the life cycle, including cost-effectiveness. Depending on the production possibilities, the decision-maker selects the prototype that is the most efficient in terms of quality–environment–cost at the same time.

3. Illustration and Test of Model

The model was illustrated and tested in accordance with the adopted methodology, i.e., in seven main stages. The possibilities of using the model were synthetically presented, including the results obtained at its individual stages.

In the first stage, the product for analysis was selected. The subject of the study was photovoltaic panels (PV), which are considered key products in mitigating negative climate change, including global warming [54]. It was decided to analyse PV because there is a lack of research in the area of improving their quality while taking into account their environmental impact on the life cycle and costs [55]. Photovoltaic panels are the most popular renewable energy source (RES) products among customers [56], and the increase in their installations over the past decade has increased by 90% (from 104 to 1053 GW) [57].

Next, during the second stage, the voice of customers was obtained regarding the quality attributes of photovoltaics. For this purpose, a pilot survey was conducted among ten customers who have or plan to buy PV. This sample was considered sufficient to test the concept of the model. Customers indicated the PV attributes that they considered important, including determining their importance. After standardising customer expectations and

assigning weights to attributes on a Likert scale, it was concluded that the following are very important to customers: efficiency, power, and energy transfer capabilities. The important attributes are the achieved temperature and the number of cells. The attributes of medium importance are dimensions and colour. The attributes of little importance are weight and electrical parameters. These attributes in the given groups had weights of five, four, three, and two, respectively.

Later, as stated in the third stage of the model, customer expectations were transformed into technical criteria, i.e., measurable criteria used by designers. This meant determining the equivalents of customer attributes in terms of technical criteria used by experts in the PV improvement process. The technical criteria were selected based on publicly available catalogues for this type of product; therefore, although efficiency includes power, voltages, or currents, they were recorded as separate criteria with their own measurement parameters. Technical criteria were assigned weights adequately to their corresponding weights in terms of customer attributes, as shown in Table 2.

Table 2. PV technical criteria and their weightings taking into account customer requirements.

Customer Attributes	Selected PV Technical Criteria	Weight (Importance)
Efficiency Power Possibility of transferring energy	Module efficiency (%) Nominal maximum power (W) Open circuit voltage (V) Voltage at maximum power point (V) Maximum static load, front (Pa) Maximum static load, rear (Pa)	5
Temperature reached Number of cells	Normal cell operating temperature (°C) Number of cells (szt.)	4
Dimensions Colour	Length × width × height (mm) Colour	3
Weight Electrical parameters	Mass (kg) Current at maximum operating point (A) Open circuit voltage (V) Short circuit current (A)	2

As a result, fourteen technical criteria were selected, the characteristics of which are as follows [58–60]:

- Module efficiency (%)—the ability of the installation to convert solar radiation into electrical energy;
- Nominal maximum power (W)—power achieved under test conditions, achieved in short periods of time during use;
- Open circuit voltage (V)—the voltage of the current that occurs when the PV is not connected to any load;
- Voltage at the maximum power point (V)—working voltage related to the maximum power;
- Maximum static load, front (Pa)—load resulting from atmospheric factors, for example, snow, wind;
- Maximum static load, rear (Pa)—load resulting from atmospheric factors, e.g., wind;
- Normal cell operating temperature (°C)—the operating temperature of the photovoltaic panel during normal use;
- Number of cells (pcs.)—the number of cells installed in one photovoltaic panel;
- length × width × height (mm)—the size of the photovoltaic panel;
- Colour—Colour of the photovoltaic panel and its frame;
- mass (kg)—total weight;
- Current at the maximum operating point (A)—operating current;

- Open circuit voltage (V)—voltage of the current when the panel is not connected to any load;
- Short circuit current (A)—current intensity during maximum load.

Based on technical criteria, a reference photovoltaic panel was adopted, i.e., a generalisation of PV of a given type. On this basis, photovoltaic prototypes were developed, which are alternative production solutions. The PV prototypes are presented in Table 3.

Table 3. PV prototypes.

Criteria	Ref.	P1	P2	P3	P4	P5	P6	P7	P8	P9
C1	21.20	19.80	22.10	21.40	18.90	20.50	21.00	19.00	21.80	22.50
C2	502	503	501	504	503	502	501	505	504	505
C3	45.70	45.50	44.90	45.60	44.75	44.65	45.70	45.50	44.80	44.95
C4	38.52	38.76	38.44	38.90	38.20	39.00	37.75	37.85	37.95	38.48
C5	5300	5350	5400	5450	5250	5200	5400	5300	5250	5400
C6	2300	2350	2400	2450	2250	2200	2400	2300	2250	2400
C7	45	46	47	42	43	44	46	47	44	46
C8	130	131	132	133	129	128	127	130	133	131
C9	2090 × 1130 × 30	2085 × 1135 × 30	2065 × 1120 × 40	2070 × 1200 × 35	2090 × 1130 × 30	2085 × 1135 × 30	2085 × 1130 × 40	2065 × 1120 × 40	2090 × 1130 × 30	2070 × 1200 × 35
C10	Black	Black	Black	Graphite	Graphite	Graphite	White	White	White	Black
C11	24	25	24	26	22	23	27	25	24	20
C12	13.09	13.10	13.12	13.07	13.13	13.08	13.11	13.05	14.00	13.15
C13	42.79	42.66	42.36	42.70	41.85	41.44	42.27	41.63	41.57	42.30
C14	11.33	11.20	11.42	11.31	11.47	11.29	10.95	10.82	10.49	10.92

where: Ref.—Reference PV, P1–P9 prototypes, C1—Module efficiency (%), C2—Nominal maximum power (W), C3—Open circuit voltage (V), C4—Voltage at maximum power point (V), C5—Maximum static load, front (Pa), C6—Maximum static load, rear (Pa), C7—Normal operating cell temperature (°C), C8—Number of cells (pcs), C9—Length × width × height (mm), C10—Colour, C11—Weight (kg), C12—Current at maximum operating point (A), C13—Open circuit voltage (V), C14—Short circuit current (A).

The reference photovoltaic and nine prototypes were developed. Subsequently, as assumed in the fifth stage of the model, their prospective quality assessment was performed. The CRITIC method was used for this purpose. Taking into account the weights of the technical criteria, including the use of Formulas (1)–(3), a matrix of absolute prototype assessments was developed. As stated in the CRITIC method, each of the vectors in the absolute assessments of the PV prototype values is characterized by a standard deviation, which presents the intensity of differences between the prototypes. Therefore, the standard deviation of the absolute prototype evaluations was calculated, as shown in Table A1.

Later, a symmetric matrix was developed, which had generic elements, i.e., those that have a linear correlation coefficient between the previous values of absolute scores (so-called vectors). This is presented in Table A2. Next, using Formula (4), the value of the so-called conflict measure between prototypes is calculated, as in Table A3.

Then, calculations were performed for the multiplicative quantification measure, as in Formula (5). Then, using Formula (6), the values obtained were normalized. In this way, a ranking of PV prototypes assessed in terms of the quality of technical criteria was obtained. The result is presented in Table 4.

According to the Q index, the quality of the PV prototypes was determined considering the customer requirements. The higher the index, the more beneficial the prototype, where, in this case, it is the P8 prototype. It has the highest quality index among the others; therefore, it can be considered the most satisfying to customers.

Next, a prospective life cycle assessment of the photovoltaic panel prototypes is carried out. The LCA was carried out according to the ‘cradle to grave’ approach, that is, taking into account the phases of material extraction and processing, production, use and end of life. The analysis was based on the guidelines of the ISO 14040 standard. The LCA was carried out using the Ecoinvent 3.10 database in the OpenLCA 2.0.0 programme [61]. Since in the offered case, the application of the LCA method concerns modelling data as part of the prospective assessment of PV prototypes, it is implemented in a basic way so as to obtain a reliable indicator of the environmental burden of the LCA for testing the model.

Therefore, based on the studies of the authors, that is, refs. [62–65], it was assumed that the functional unit is the production of 1 kWh of PV electricity. On the other hand, the system boundaries take into account the aforementioned LCA phases, which were limited to Europe and the data presented in [66], including data from the Ecoinvent 3.10 database. The boundaries of the adopted system are presented in Figure 3.

Table 4. Ranking of PV prototypes by quality index.

Product	O	Q	Ranking
Ref.	2.32	0.19	9
P1	1.82	0.00	10
P2	3.06	0.46	4
P3	2.98	0.43	6
P4	2.55	0.27	8
P5	2.80	0.36	7
P6	3.53	0.63	2
P7	3.38	0.58	3
P8	4.52	1.00	1
P9	2.93	0.41	5

where: Ref.—PV reference, P1–P9—PV prototypes, O—quantifying measure, Q—quality of prototype.

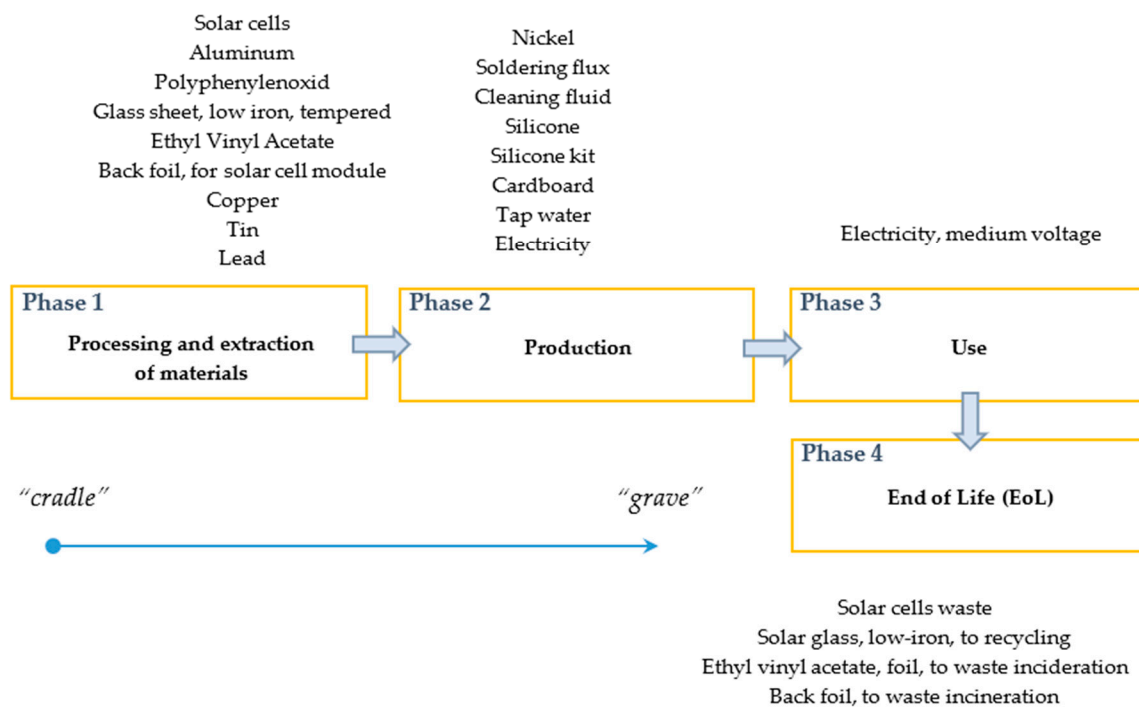


Figure 3. System boundary. Own study based on [66].

The inventory data concern materials, electricity and waste, which are used, e.g., for connecting cells, creating and fixing PV frames (copper, silicon), rinsing glass (water), laminating, testing (electricity), etc. The carbon footprint (CF) criterion was selected as the environmental burden, derived from the ecological footprint [67]. The carbon footprint is the total amount of carbon dioxide (CO₂) emissions that are directly and indirectly caused by the product [68]. In the case of LCA, it is presented as the so-called carbon dioxide equivalent (eCO₂) [69].

Based on [66], the inventory data for the reference PV were adopted, and in accordance with them, the expert team determined the inventory data modelled prospectively for the PV prototypes, as shown in Table 5.

Table 5. Modelled inventory data of PV prototypes.

Data	Ref.	P1	P2	P3	P4	P5	P6	P7	P8	P9
E1	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
E2	59.050	44.395	88.173	28.710	63.691	63.718	25.357	72.659	62.099	59.050
E3	4.052	4.603	4.262	3.447	3.847	3.654	1.970	1.740	3.047	4.574
E4	0.289	0.432	0.356	0.312	0.218	0.289	0.304	0.246	0.312	0.124
E5	15.534	14.747	17.535	17.646	15.534	7.553	14.006	16.755	19.115	23.196
E6	2.345	2.466	1.994	2.530	2.647	2.114	2.663	2.345	2.529	1.140
E7	0.174	0.148	0.131	0.259	0.084	0.075	0.196	0.187	0.165	0.214
E8	0.009	0.009	0.009	0.004	0.013	0.010	0.009	0.009	0.007	0.008
E9	0.005	0.004	0.004	0.005	0.005	0.006	0.005	0.002	0.002	0.005
E10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
E11	0.013	0.011	0.019	0.011	0.014	0.014	0.014	0.015	0.014	0.009
E12	0.020	0.023	0.022	0.021	0.018	0.009	0.017	0.022	0.019	0.010
E13	0.188	0.188	0.214	0.169	0.281	0.160	0.203	0.178	0.212	0.203
E14	1.689	1.269	1.918	1.689	2.078	0.821	2.521	1.522	1.822	0.725
E15	32.806	40.366	34.499	15.950	27.905	35.384	29.577	31.143	37.266	14.087
E16	20.610	22.239	8.850	17.531	15.495	21.674	23.412	30.774	23.264	25.360
E17	0.012	0.011	0.013	0.018	0.006	0.012	0.013	0.009	0.012	0.013
E18	0.154	0.167	0.147	0.066	0.131	0.116	0.162	0.154	0.175	0.139
E19	0.116	0.173	0.056	0.142	0.132	0.050	0.098	0.125	0.110	0.087

where: E1—Module, c-Si (p), E2—Solar cells (p), E3—Aluminium (kg), E4—Polyphenylenoxid (kg), E5—Glass sheet, low iron, tempered (kg), E6—Ethyl Vinyl Acetate + black foil (kg), E7—Copper (kg), E8—Tin (kg), E9—Lead (kg), E10—Nickel (kg), E11—Soldering flux (kg), E12—Cleaning fluid (kg), E13—Silicone + silicone kit (kg), E14—Cardboard (kg), E15—Tap water (kg), E16—Electricity, medium voltage (kWh), E17—Solar cells waste (kg), E18—Solar glass, low-iron, to recycling (kg), E19—Ethyl vinyl acetate, foil, to waste incineration (kg).

Using the Ecoinvent database in OpenLCA, the environmental impact (EI) of the PV prototypes in the life cycle was estimated for the carbon footprint categories. Using Formula (7), the values obtained were normalised to present the final LCA index. On this basis, a classification of the PV prototypes was developed according to their expected negative impact on the life cycle, as shown in Table 6.

Table 6. Ranking of PV prototypes by environmental index.

Product	EI	LCA	Ranking
Ref.	891.03	0.66	5
P1	841.58	0.76	4
P2	984.35	0.49	9
P3	768.48	0.90	2
P4	1239.91	0.00	10
P5	713.80	1.00	1
P6	915.01	0.62	7
P7	822.65	0.79	3
P8	963.26	0.53	8
P9	901.54	0.64	6

where: Ref.—PV reference, P1–P9—PV prototypes, EI—environmental impact, LCA—life cycle assessment index.

It was observed that the most advantageous in this case is the P4 prototype. It has the lowest environmental burden of carbon dioxide emissions in the PV life cycle. Next, the P3 prototype is relatively advantageous. The least advantageous was the P4 prototype. However, within the offered model, the direction of PV improvement includes cost analysis, according to the CEA method.

Therefore, in the seventh stage of the model, a cost-effectiveness analysis (CEA) was applied. The aim was to estimate the cost incurred within the quality coverage of the photovoltaic prototype taking into account its environmental burden in the life cycle (LCA). Initially, the expert team estimates the prototype cost, which is subsequently normalised for further processing with the quality indicator (Q) and the environmental burden in the life

cycle (LCA). Formula (8) is used for this purpose, and the result is presented in Table A4. Then, the quality indicator (Q) is aggregated with the environmental burden in the life cycle (LCA) indicator into a quality–environmental indicator (QLCA), as in Formula (9). Based on the QLCA indicator and the normalised cost values (C), the cost-effectiveness of the PV prototypes is estimated in terms of quality–environment–cost, according to Formula (9). Based on the ICER–QLCA indicator, a ranking of PV prototypes was developed, as shown in Table 7.

Table 7. Ranking of PV prototypes according to the ICER–QLCA index.

Product	QLCA	C	ICER–QLCA	Ranking
P8	0.76	0.08	−2.71	3
P7	0.69	0.17	−3.19	4
P5	0.68	0.83	−0.65	1
P3	0.66	0.13	−3.65	5
P6	0.63	0.00	−4.98	6
P9	0.53	0.75	−2.42	2
P2	0.47	0.25	−15.58	8
Ref.	0.42	1.00	2.36	7
P1	0.38	0.83	3.65	9
P4	0.14	0.92	0.29	10

where: Ref.—PV reference, P1–P9—PV prototypes, QLCA—aggregated quality–environmental index, C—cost, ICER–QLCA—quality–environment–cost index.

As part of the comprehensive analysis of the results, a decision matrix was developed using the assumptions of Formulas (10) and (11), including the development of a linear indicator function, as shown in Figure 4.

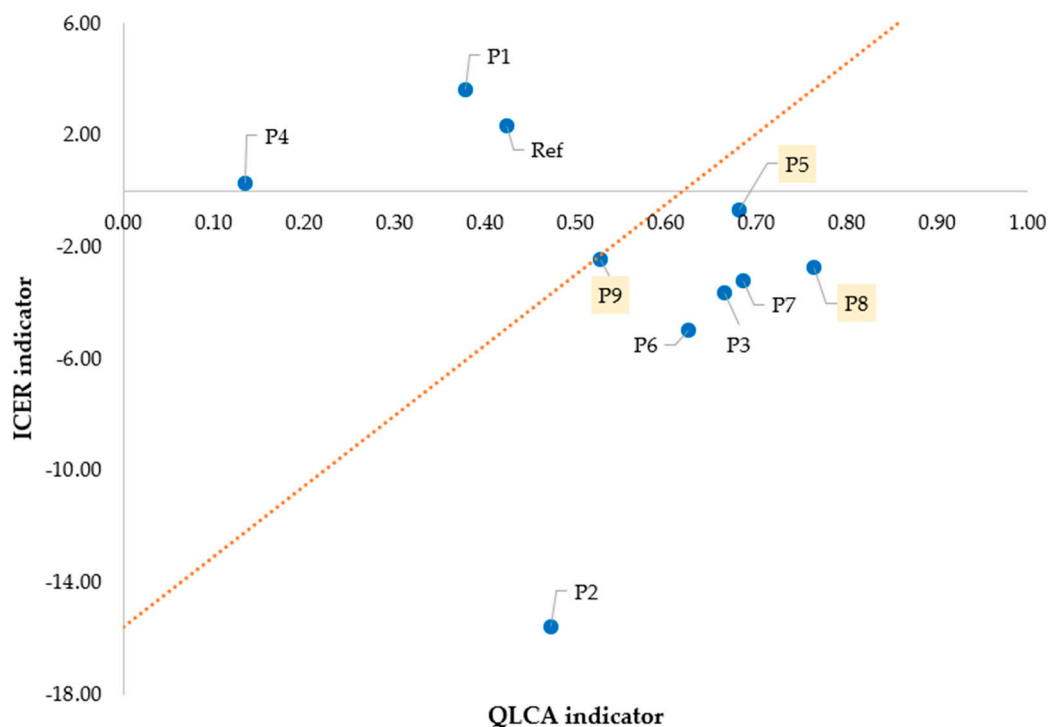


Figure 4. Quality–environment–cost analysis according to the ICER–QLCA index.

The most advantageous was observed to be the prototype P5 (first position in the ranking), followed by the prototype P9 (second position in the ranking) and the prototype P8 (third position in the ranking). The least advantageous is the prototype P4 (last position in the ranking). Therefore, it is reasonable to consider taking action to improve photovoltaic energy to achieve the design assumptions adopted for the prototype P5. If this were

not possible, e.g., in terms of finances or availability of other resources, then the next prototypes should be considered, e.g., P9 or P8, or others from the area of “cost-effective production solutions”.

An in-depth expert analysis can be performed to consider the selection of a manufacturable prototype, e.g., due to resource availability, by considering the three most cost-effective manufacturing solutions, e.g., in a morphological matrix, as shown in Figure 5.

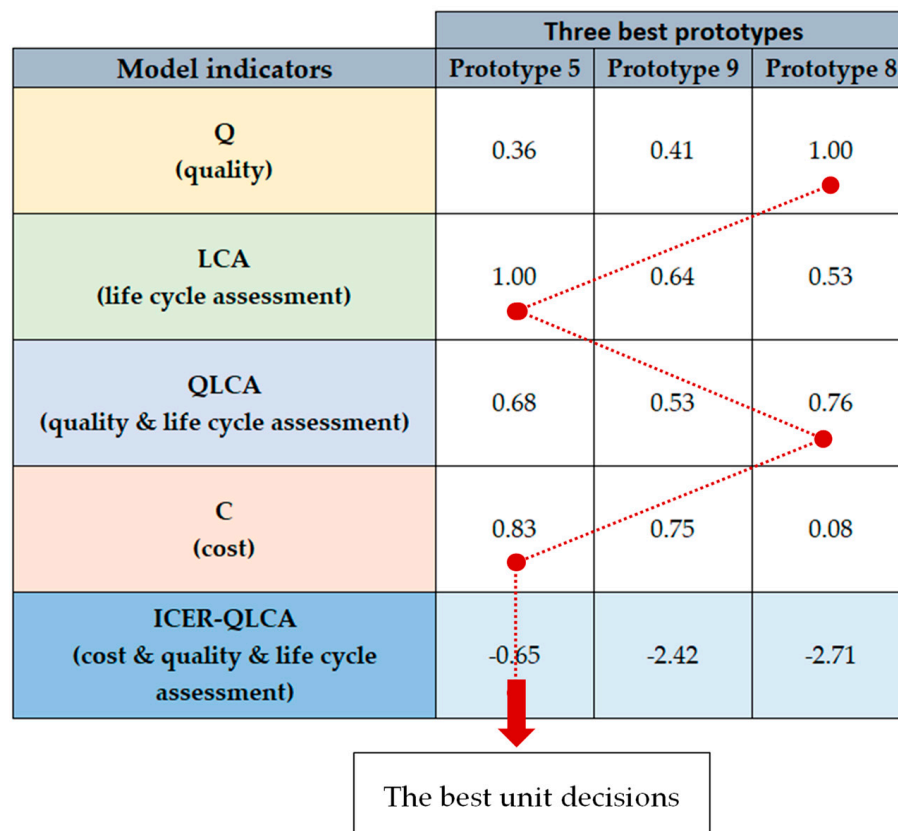


Figure 5. Analysis of production solutions of PV according to individual model indicators using the morphology matrix.

Morphological analysis showed that favourable production solutions appeared more often in the case of prototype P5 and prototype P8. In terms of quality, P8 was the most favourable. In turn, P5 turned out to be the most friendly. However, taking into account both quality and environmental burden in the life cycle, the most appropriate was the prototype with a higher quality index, i.e., P8. This results from the relatively low-quality index for the aforementioned P5. Taking into account the purchase cost, while considering quality and environmental burden in the life cycle, the P5 prototype is ultimately indicated as the most optimal production solution.

It should be remembered that the results obtained from the model will depend on the expectations of customers, including the needs and expert knowledge of the people using the model. At the same time, in the case under consideration, the results are modelled as an illustration and test of the model’s concept and methodology. Therefore, they may vary depending on the specifics of their application. Furthermore, it can be observed that the product ranking and the indicators obtained in it can be considered with regard to its importance in the overall design and production process, which can also generate other design decisions. However, the model test confirmed its efficiency within the framework of sustainable product development using the example of photovoltaic panels.

A detailed analysis of the model sensitivity was performed as part of the Section 4 on the results of the proposed approach.

4. Discussion

As suggested in the study [13], understanding the potential and production possibilities of renewable energy sources (RES) is an essential element in the further development of clean and stable products that generate green energy. An important issue is, for example, the investment cost in RES products, which is important not only from the manufacturer's point of view, but also from the customer's point of view, because it translates into the final cost of the product, including the purchase cost [70]. However, the development of RES products should meet market requirements, which is manifested by ensuring customer satisfaction with the RES products offered, as confirmed, for example, in [71,72]. Development decisions should also take into account environmental aspects, especially now in the era of increased climate change and global warming [73]. Therefore, it is reasonable to take environmentally friendly actions, e.g., within the framework of the life cycle assessment of RES products [74]. Despite the knowledge of the principles consistent with the sustainable development of products, there is still a lack of coherent approaches and methods supporting the improvement processes so that they simultaneously take into account the criteria of quality, environment, and cost. Therefore, the objective of the research was to develop a decision-making model supporting eco-innovation in products based on quality, cost, and life cycle assessment (LCA). The model was tested on an example of photovoltaic panels, which are elementary RES products. As part of a detailed discussion of the model results, they are summarised in Table 8.

Table 8. Comparison of model results according to the obtained decision metrics with rankings for PV prototypes.

Product	Q	Ranking	LCA	Ranking	QLCA	Ranking	C	Ranking	ICER-QLCA	Ranking
Ref.	0.19	9	0.66	5	0.42	8	1.00	1	2.36	7
P1	0.00	10	0.76	4	0.38	9	0.83	3	3.65	9
P2	0.46	4	0.49	9	0.47	7	0.25	5	−15.58	8
P3	0.43	6	0.90	2	0.66	4	0.13	7	−3.65	5
P4	0.27	8	0.00	10	0.14	10	0.92	2	0.29	10
P5	0.36	7	1.00	1	0.68	3	0.83	3	−0.65	1
P6	0.63	2	0.62	7	0.63	5	0.00	9	−4.98	6
P7	0.58	3	0.79	3	0.69	2	0.17	6	−3.19	4
P8	1.00	1	0.53	8	0.76	1	0.08	8	−2.71	3
P9	0.41	5	0.64	6	0.53	6	0.75	4	−2.42	2

where: Ref.—PV reference, P1–P9—PV prototypes, Q—quality, LCA—life cycle assessment, QLCA—quality-life cycle assessment, C—cost, ICER-QLCA—quality–environment–cost index.

It was observed that the first position of the prototypes in the rankings changed at the individual stages of the model. Accordingly, the first position in the rankings was occupied by P8 (Q), P5 (LCA), P8 (QLCA), Ref. (C), and P6 (ICER-QLCA). Despite the fact that the P8 prototype was the most advantageous twice, it was unable to maintain this position in the final ranking. Taking into account the results for the second place in the rankings, the following were obtained: P6 (Q), P3 (LCA), P7 (QLCA), P4 (C), and ICER-QLCA (P9). On the other hand, for the third place in the rankings, the following were obtained: P7 (Q), P7 (LCA), P5 (QLCA), P1 (C), and P8 (ICER-QLCA). In connection with this, it was shown that depending on the interpreted decision criterion, the model can support development decisions in terms of quality, environment, and cost. Initially, it was also concluded that the model is sensitive and effectively selects, orders, and distinguishes indicator values depending on the interpreted decision criterion.

However, in order to reliably check the sensitivity of the model, an additional global analysis of the model sensitivity was carried out in Statistica 13.3. The aim was to assess post factum the impact of the values of the indicators obtained at the individual stages of the model on the final quality–environment–cost indicator, including the ranking of PV prototypes. At the same time, it was assumed to differentiate the degree of impact of the model indicators on the final decision indicator (ICER-QLCA). Due to the type of data, it

was decided to use regression analysis. The random sampling method was used, where the number of random samples was as follows: 70% training, 15% testing, and 15% validation. The initial value of the generator was set to 1000 [75]. According to these assumptions, the construction of the neural network was started. The input elements were the model indicators obtained at its individual stages, i.e., quality indicator (Q), environmental burden indicator in the life cycle (LCA), aggregated quality–environmental indicator (QLCA), and normalised cost indicator (C). However, the final decision indicator ICER–QLCA was adopted in the output, which simultaneously takes into account the normalised quality–environmental indicator and the cost indicator. After testing the neural networks, it was decided to use the MLP 4-3-1 network, which has four input neurones, three neurones in the hidden layer, and one neurone at the output. It is characterised by a learning quality of 99% with an error of 0.01. The results of the global analysis of the model sensitivity are presented in Table 9.

Table 9. Global model sensitivity analysis.

Indicator	Q	LCA	QLCA	C
MLP 4-3-1	140.35	42.47	34.49	181.15
Impact on ICER–QLCA ranking	2	3	4	1

The model was observed to function correctly, and all the indicators included in it had an impact on the final ICER–QLCA indicator, because they were greater than 1 [75]. It was shown that the normalised cost indicator had the greatest impact on the final ranking. The quality indicator had a significant impact. The environmental indicator had a smaller but equally significant impact on the final ranking, and then its aggregated form with the quality indicator. This confirmed that the model is sensitive to variables, i.e., it is able to detect the tested feature or detect its absence.

The main expected benefits of the offered model include the following:

- the possibility of improving product quality with the customer’s voice (VoC) in mind;
- prospective assessment of the environmental burden of the product based on the environmental assessment of the current (reference) product and anticipated production changes;
- interpretation of the direction of product development according to the simultaneous consideration of achieving the product quality expected by customers and ensuring an environmentally friendly product;
- estimation of the profitability of investment in product development at the prototyping stage, taking into account not only financial aspects (cost) but also the quality of the product and its impact on the environment in the life cycle (LCA).

The developed model also has business benefits, including providing support to managers and decision-makers, for example:

- supporting decisions in the early stages of product development, including during its improvement;
- streamlining the company’s preparatory activities for investments related to product development in terms of quality, environment and cost;
- ensuring the ranking of production solutions and searching for alternative production solutions towards sustainable product development;
- reducing the waste of company resources as a result of assistance in well-considered development decisions taking into account key criteria of sustainable development.

On the other hand, one limitation of the model is its adaptation to the analysis of one criterion of environmental burden within one product analysis. This is also a kind of advantage, because it directs the analysis to the basic environmental burden from the point of view of a given product. However, in the case of complex products, this can be a limitation and cause deficiencies in the assessment of the environmental impact. Additionally, the offered model focuses on modelling data, mainly from the environmental

point of view within the prospective assessment of product prototypes. Therefore, the results constitute a kind of estimate of the environmental burden, which, due to the nature of the model, seems to be sufficient within the framework of predicting improvement actions consistent with sustainable development.

In future research, it is planned to extend the model to include other criteria of sustainable development. Additionally, it is planned to develop assumptions for selecting the weights of the model criteria and then implement the next stage of the model in the currently created one. Then, with its participation, it will be possible to dynamically generate a ranking of prototypes depending on the individual preferences of the expert regarding the importance of decision criteria (quality, environment, cost).

5. Conclusions

The purpose of the research was to develop a model that supports the search for eco-innovative product solutions for their sustainable development. The functioning of the model was based on eight main stages: (1) Inspiration and selection of the research subject, (2) Obtaining the voice of customers regarding product attributes, (3) Identification of technical criteria, (4) Development of product prototypes, (5) Prospective assessment of the quality of product prototypes, (6) Prospective assessment of the life cycle of prototypes (LCA), (7) Cost-effectiveness analysis (CEA), (8) Interpretation of results and setting the direction of improvement actions.

The model is based on various techniques supporting its use, for example: a survey to obtain customer expectations, the 7 ± 2 principle of 73 of effective decision support, brainstorming (BM) and teamwork, the CRITIC method to assess the quality of prototypes, the ISO 14040 standard and the Ecoinvent database in the OpenLCA programme to assess the environmental burden of prototypes throughout their life cycle (LCA), cost-effectiveness analysis (CEA) to take into account the cost of investment in the prototype with the simultaneous interpretation of quality and environmental aspects.

The model test and illustration were presented using photovoltaic (PV) panels as an example. A reference PV was developed, including nine different prototypes. As a result, the most advantageous production solutions were identified, which included high customer satisfaction with the quality of PV, limited negative environmental impact in the life cycle, and a profitable investment cost. This approach supports sustainable PV development, including being the basis for creating eco-innovations in these types of products.

This model is better than previous solutions because it allows for prospective analysis of various production solutions of products in terms of their sustainable development. It supports simultaneous analysis of key criteria, i.e., quality (fulfilment of customer satisfaction with use), environmental impact (environmental burden in the life cycle) and investment cost. On their basis, it is possible to predict favourable production solutions that will meet the above criteria to the greatest possible extent, and thus contribute to the development of eco-innovative solutions on the market of offered products. The entire process is supported by appropriately selected techniques, including decision support methods, which are selected in an original and previously unpractised way.

The offered model is dedicated to manufacturing companies, including decision-makers and managers in the early stages of product development, and especially in the improvement process. It supports the adoption of eco-innovative product solutions that will simultaneously meet the expected quality, environmental, and cost criteria in the best possible way. The analysed approach allowed the selection of a photovoltaic prototype that simultaneously meets the indicated criteria to the greatest possible extent. It was the prototype P8, whose results are as follows: quality index $Q = 0.36$ (seventh place in the ranking), environmental burden index $LCA = 1.00$ (first place in the ranking), quality–environmental index $QLCA = 0.68$ (third place in the ranking), price index $C = 0.83$ (third place in the ranking), and price–quality–environmental index $ICER-QLCA = -0.65$ (first place in the ranking). Therefore, the model can be useful for making good development decisions in terms of sustainable product development.

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Appendix A

Table A1. Absolute quality assessments of technical criteria of PV prototypes.

Criteria	Ref.	P1	P2	P3	P4	P5	P6	P7	P8	P9
C1	0.64	0.25	0.89	0.69	0.00	0.44	0.58	0.03	0.81	1.00
C2	0.25	0.50	0.00	0.75	0.50	0.25	0.00	1.00	0.75	1.00
C3	1.00	0.81	0.24	0.90	0.10	0.00	1.00	0.81	0.14	0.29
C4	0.62	0.81	0.55	0.92	0.36	1.00	0.00	0.08	0.16	0.58
C5	0.40	0.60	0.80	1.00	0.20	0.00	0.80	0.40	0.20	0.80
C6	0.40	0.60	0.80	1.00	0.20	0.00	0.80	0.40	0.20	0.80
C7	0.60	0.80	1.00	0.00	0.20	0.40	0.80	1.00	0.40	0.80
C8	0.50	0.67	0.83	1.00	0.33	0.17	0.00	0.50	1.00	0.67
C9	1.00	0.67	0.00	0.33	1.00	0.67	0.67	0.00	1.00	0.33
C10	1.00	1.00	1.00	0.50	0.50	0.50	0.00	0.00	0.00	1.00
C11	0.57	0.71	0.57	0.86	0.29	0.43	1.00	0.71	0.57	0.00
C12	0.04	0.05	0.07	0.02	0.08	0.03	0.06	0.00	1.00	0.11
C13	1.00	0.90	0.68	0.93	0.30	0.00	0.61	0.14	0.10	0.64
C14	0.86	0.72	0.95	0.84	1.00	0.82	0.47	0.34	0.00	0.44
St. dev.	0.31	0.25	0.37	0.35	0.31	0.33	0.39	0.37	0.39	0.33

where: St. dev.—Standard deviation, Ref.—PV reference, P1–P9 prototypes, C1—Module efficiency (%), C2—Nominal maximum power (W), C3—Open circuit voltage (V), C4—Voltage at maximum power point (V), C5—Maximum static load, front (Pa), C6—Maximum static load, rear (Pa), C7—Normal operating cell temperature (°C), C8—Number of cells (pcs), C9—Length × width × height (mm), C10—Colour, C11—Weight (kg), C12—Current at maximum operating point (A), C13—Open circuit voltage (V), C14—Short circuit current (A).

Table A2. Symmetric matrix with generic elements having linear correlation coefficient corresponding to absolute quality ratings of PV prototype criteria.

Product	Ref.	P1	P2	P3	P4	P5	P6	P7	P8	P9
Ref.	1.00	0.72	0.21	0.14	0.42	0.32	0.28	−0.20	−0.45	−0.01
P1	0.72	1.00	0.37	0.30	0.33	0.24	0.15	0.17	−0.67	0.12
P2	0.21	0.37	1.00	0.21	−0.13	0.12	0.11	−0.06	−0.50	0.45
P3	0.14	0.30	0.21	1.00	−0.04	−0.11	0.12	0.08	−0.38	0.13
P4	0.42	0.33	−0.13	−0.04	1.00	0.59	−0.17	−0.16	−0.05	−0.11
P5	0.32	0.24	0.12	−0.11	0.59	1.00	−0.27	−0.26	−0.09	−0.03
P6	0.28	0.15	0.11	0.12	−0.17	−0.27	1.00	0.32	−0.23	−0.29
P7	−0.20	0.17	−0.06	0.08	−0.16	−0.26	0.32	1.00	−0.03	0.03
P8	−0.45	−0.67	−0.50	−0.38	−0.05	−0.09	−0.23	−0.03	1.00	−0.19
P9	−0.01	0.12	0.45	0.13	−0.11	−0.03	−0.29	0.03	−0.19	1.00

where: Ref.—PV reference, P1–P9—PV prototypes.

Table A3. Measure of conflict between PV prototypes determined based on quality assessments of technical criteria.

Product	Ref.	P1	P2	P3	P4	P5	P6	P7	P8	P9
Ref.	0.00	0.28	0.79	0.86	0.58	0.68	0.72	1.20	1.45	1.01
P1	0.28	0.00	0.63	0.70	0.67	0.76	0.85	0.83	1.67	0.88
P2	0.79	0.63	0.00	0.79	1.13	0.88	0.89	1.06	1.50	0.55
P3	0.86	0.70	0.79	0.00	1.04	1.11	0.88	0.92	1.38	0.87
P4	0.58	0.67	1.13	1.04	0.00	0.41	1.17	1.16	1.05	1.11
P5	0.68	0.76	0.88	1.11	0.41	0.00	1.27	1.26	1.09	1.03
P6	0.72	0.85	0.89	0.88	1.17	1.27	0.00	0.68	1.23	1.29
P7	1.20	0.83	1.06	0.92	1.16	1.26	0.68	0.00	1.03	0.97
P8	1.45	1.67	1.50	1.38	1.05	1.09	1.23	1.03	0.00	1.19
P9	1.01	0.88	0.55	0.87	1.11	1.03	1.29	0.97	1.19	0.00

where: Ref.—PV reference, P1–P9—PV prototypes.

Table A4. Estimated cost of PV prototypes and their normalized value.

Product	Cost (PLN)	C
Ref.	280.00	1.00
P1	300.00	0.83
P2	370.00	0.25
P3	385.00	0.13
P4	290.00	0.92
P5	300.00	0.83
P6	400.00	0.00
P7	380.00	0.17
P8	390.00	0.08
P9	310.00	0.75

where: Ref.—PV reference, P1–P9—PV prototypes, C—normalized cost.

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