energies

Article

Balanced-Scorecard-Based Evaluation of Knowledge-Oriented Competencies of Distributed Energy Investments

Elias Carayannis [1], Pantelis Kostis [2,*], Hasan Dinçer [3] and Serhat Yüksel [3]

[1] School of Business, George Washington University, Washington, DC 20052, USA
[2] Department of Economics, National and Kapodistrian University of Athens, 15559 Athens, Greece
[3] The School of Business, İstanbul Medipol University, Istanbul 34810, Turkey
* Correspondence: pkostis@econ.uoa.gr; Tel.: +30-210-3689-432

Abstract: Since the global warming problem threatens the whole world, it is understood that countries should develop energy policies that will increase their sustainable and clean energy investments. Compared to other alternatives, the high cost of renewable energy projects is an essential obstacle in this process. Therefore, priority should be given to developing distributed energy projects to minimize this problem. The scope of the present paper is to identify the most critical items that affect the performance of distributed energy projects to have knowledge-oriented competencies. In this way, companies can focus on more critical items to provide efficiency for distributed energy projects. As a result, clean energy usage is improved, and the global warming problem is handled more successfully. A novel decision-making model is generated to examine the competencies of the knowledge economy based on collaborative filtering and bipolar q-rung orthopair fuzzy sets (q-ROFSs) with the golden ratio. The analysis concludes that learning and growth are the most critical balanced scorecard perspectives. Moreover, it was also determined that information and communication technology is the most critical competency of the knowledge economy. Therefore, it would be appropriate for investors who plan to invest in distributed energy projects to form a research and development team. Hence, new technologies will be followed instantly. In this way, companies will be able to gain a cost advantage. In this context, improving distributed energy projects is important to increase efficiency in clean energy investments.

Keywords: distributed energy investments; clean energy; renewable energy; balanced scorecard

check for updates

Citation: Carayannis, E.; Kostis, P.; Dinçer, H.; Yüksel, S. Balanced-Scorecard-Based Evaluation of Knowledge-Oriented Competencies of Distributed Energy Investments. *Energies* **2022**, *15*, 8245. https://doi.org/10.3390/en15218245

Academic Editor: Idiano D'Adamo

Received: 13 October 2022
Accepted: 3 November 2022
Published: 4 November 2022

1. Introduction

Global warming is mainly caused by carbon emissions resulting from the use of fossil fuels. Obtaining energy by burning resources such as coal and oil causes significant environmental damage. To solve this problem, countries are trying to increase the use of renewable energy or to develop new ways of energy generation, such as fusion energy [1]. These projects must be economically efficient to provide the continuity of clean energy use [2]. It is crucial to increase these investments' profitability by reducing the projects' costs. Another way to increase the efficiency of clean energy projects is the distributed energy application. In these investments, energy production occurs at the point of consumption [3]. The primary purpose of this process is to reduce energy distribution costs [4]. Hence, it can be possible to eliminate the complexity and inefficiency problems in the process. Another benefit of distributed energy projects is that clean energy can be improved. Clean energy sources such as the sun and wind are used in homes and workplaces. In this process, decreasing costs encourages the use of clean energy that can significantly help to solve the global warming problem.

For distributed energy projects to succeed, investors must have knowledge-oriented competencies [5]. Distributed energy investments are projects that involve complex processes, especially in the current uncertain environment [6]. Therefore, investors need to have sufficient knowledge of many different processes. In other words, for these investments to be successful, investors need to develop themselves in different aspects. In this process, knowledge-oriented competencies play a very important role. For example, enterprises should have competent personnel. In this way, businesses will be more likely to innovate more effectively [7]. In addition, it will be important for businesses to have the necessary technical equipment. This will help increase the performance of distributed energy projects. Whether the work has an innovation potential or not is another issue to be considered in this context [8]. Investments in energy types that need more potential may create inefficiency. Legal regulations in countries also play a crucial role in enabling distributed energy projects to have knowledge-oriented competencies [9].

Moreover, some factors must be considered for successful distributed energy investments. Financial analysis has a vital role in this process. Projects without a comprehensive cost-benefit analysis will likely incur losses [10]. For these projects to be successful, customer expectations must also be met clearly. This will help to increase customer satisfaction, and in this way, the enterprises' products will be better preferred. Organizational efficiency is another critical issue in this context. Furthermore, businesses need to follow innovations carefully and implement them quickly for performance improvement [11].

In summary, for distributed energy projects to be successful, they need to have knowledge-oriented competencies and take the necessary actions to increase their performance. Since each improvement to be made within the companies means investment, it will cause the costs of these companies to increase. When the studies in the literature are examined, it is seen that comprehensive analyses have been made on the factors affecting the performance of distributed energy projects [12]. However, there are limited studies that determine which factor is more important [13]. Therefore, there is a need for a new study that will identify the most critical issues for distributed energy projects to have knowledge-oriented competencies.

Accordingly, this study proposes a unique decision-making model for evaluating the competencies of the knowledge economy. Firstly, collaborative filtering is adapted to the decision-making methodology to input the preliminary evaluations of the decision-makers. Secondly, the extension of the Stepwise Weight Assessment Ratio Analysis (SWARA) entitled Multi SWARA (M-SWARA) with bipolar q-Rung Orthopair Fuzzy Sets (q-ROFSs), and the golden ratio is applied to figure out the impact-relation directions and the weights for the perspectives of a balanced scorecard with the imputed evaluations. Thirdly, the extension of the Elimination and Choice Translating Reality (ELECTRE) entitled golden ratio bipolar q-ROF ELECTRE is used to generate the possible directions among the competencies of knowledge-oriented distributed energy investments. The main novelty of this study is evaluating a critical topic for the effective energy policies of the countries with the help of an original fuzzy decision-making model. Based on the analysis results of this study, it can be possible to identify the essential items that affect the performance of distributed energy projects to have knowledge-oriented competencies. Therefore, companies can focus on more critical items to provide efficiency for distributed energy projects. This situation significantly influences clean energy usage; thus, the global warming problem can be handled more successfully. Moreover, M-SWARA is a decision-making process that can align with several themes on ecosystemic decision analytics (multi-level, multi-modal, multilateral, and multi-nodal), and, besides energy, may have critical impacts and implications on theory, policy, practice, and politics in many contexts [14].

It is also possible to mention some advantages of the proposed decision-making model. In this model, some improvements are made to the classical SWARA approach. As a result, a new technique is created by M-SWARA. The main superiority of this new approach is that causality analysis between the criteria can be identified. Additionally, the degrees in q-ROFSs are computed with the help of the golden ratio. Hence, more effective evaluations can be made that help us to reach appropriate findings. These two new improvements have a powerful impact on the originality of the proposed model. Moreover, criteria lists are created by considering the perspectives of the balanced scorecard approach. Finance, the customer, internal effectiveness, and learning and growth are the main perspectives of this approach. Hence, this technique focuses on financial and non-financial factors while managing performance. Therefore, a comprehensive factor list can be considered with the help of the balanced scorecard approach. This situation has a positive contribution to reaching more appropriate findings. Furthermore, considering the ELECTRE methodology also provides some advantages. The compensation between criteria and the normalization process can be avoided with the help of this technique. This is a way to achieve the best possible (sub-optimal feasible) trade-offs that are highly efficacious (effectively efficient).

The following part includes the evaluation of the literature for this content. Methods are explained in the third part. The results of the analysis are demonstrated in the following part. In the end, the conclusions and discussions are presented.

2. Literature on Distributed Energy Investments

Different aspects affect the development of knowledge-based competencies in distributed energy projects. First, financial analysis of these projects should be conducted effectively. Different costs characterize these projects [15]. In the financial analysis process, each cost type should be considered depending on its timing [16]. Otherwise, there will be liquidity risk in the project [17]. Managing this risk effectively may also cause the project to fail [18]. Therefore, it is crucial to conduct a cost-benefit analysis in which cash flows are evaluated comprehensively [19]. Mahani et al. [20] evaluated distributed energy projects economically and operationally. They identified that the cost-benefit evaluation of the energy storage system in these projects should be scrutinized. Harish et al. [21] also performed a socio-techno-economic analysis of distributed energy systems in India. It was determined that project cash flows should be estimated appropriately for performance improvement.

The fact that the offered products meet the customers' expectations also contributes to increasing the knowledge-based competencies of distributed energy projects. There are some complex processes in these projects [22]. Therefore, customers want to manage these comprehensive processes without experiencing any problems [23]. Any disruption that may occur in this process should be resolved quickly and efficiently by the investors [24]. Otherwise, this will create customer dissatisfaction, leading to a decrease in the performance of the project [25]. Thus, it is necessary to develop a system in which customers' problems can be resolved in a short time and effectively [26]. Liu and Ding [27] studied distributed energy resources and concluded that customer satisfaction should be satisfied for the sustainability of these projects. Chen et al. [28] aimed to generate an efficient distributed energy management system technique. They determined that the customers' expectations should be satisfied for the performance improvements.

Technological competence is vital so businesses that carry out distributed energy projects can have more knowledge-based competencies [29,30]. In these projects, applications such as solar and wind energy are carried out on much smaller scales [31,32]. Hence, to realize these issues, companies must have sufficient technological equipment [33,34]. Otherwise, there will be constant disruptions in the process, which will reduce the project's efficiency. Niu et al. [35] examined key performance indicators for the distributed energy system, concluding that companies should make technological investments for the success of these projects. Xu et al. [36] studied the driving forces of distributed energy resources in China, and they concluded that technological development is necessary for performance improvements.

Qualified personnel is also essential for developing the knowledge-based competencies of distributed energy projects [34]. Competent personnel should avoid disruptions in these projects, which involve complex engineering processes [37]. This personnel will also help to solve the problems that may arise in the projects in a timely and correct manner [38]. This issue should be considered in the personnel recruitment process [39]. Additionally, development training should be provided to the personnel working within the companies. Zalengera et al. [40] evaluated distributed energy services in sub-Saharan Africa, highlighting that investors should employ qualified personnel. Vasiliev and Alameh [41] studied distributed energy generation and concluded that for the aim of implementing recent technologies for this situation, companies should give priority to qualified personnel.

Knowledge-oriented competencies play a critical role in the performance improvement of distributed energy projects. The studies in the literature focused on the factors affecting the performance of distributed energy projects generally. However, it would be appropriate for the investors to identify the more significant factors. With the help of this issue, specific actions can be taken for them. Nevertheless, there are limited studies that determine which factor is more important. Therefore, there is a need for a new study that will identify the most critical issues for distributed energy projects to have knowledge-oriented competencies. In this context, a novel model is constructed in this study to evaluate the competencies of the knowledge economy. Owing to this situation, essential items that affect the performance of distributed energy projects to have knowledge-oriented competencies can be understood.

3. Methodology

This part indicates bipolar q-ROFSs, M-SWARA, ELECTRE, and the imputation of expert evaluations with collaborative filtering. Next, the proposed model is explained. The details of all equations are stated in Appendix A. The proposed model aims to generate an original technique by considering these approaches. Through the advantages of these methods, uncertainty in the decision-making process is minimized, so appropriate results can be achieved. Collaborative filtering helps to complete missing information when experts need an opinion about an issue. Similarly, the SWARA technique is improved in this model, and a new technique is created called M-SWARA. This new methodology helps to calculate the causal relationship between the factors. Bipolar q-ROFSs consider a much wider space by comparing with IFSs and PFSs. Thus, the uncertainty problem in this process can be handled more effectively. Moreover, the degrees in these sets are computed using the golden ratio, so the appropriateness of the findings can be increased. In addition, the balanced scorecard approach focuses on financial and non-financial factors while managing performance. This situation allows considering a comprehensive factor list [42,43].

3.1. Bipolar q-ROFSs with Golden Ratio

Atanassov [44] introduced Intuitionistic Fuzzy Sets (IFSs) by defining both membership and non-membership degrees (MMP, and NNP) that are indicated by $(\mu_I,\ n_I)$. Equation (A1) represents these sets, and the requirement is explained in Equation (A2). Yager [45] generated PFSs using a broader space in the analysis to handle uncertainties more successfully. Equations (A3) and (A4) demonstrate the condition and requirement. With their combination, q-ROFSs were developed by Yager [46] with new degrees $(\mu_q,\ n_q)$. Equations (A5) and (A6) explain the details and requirements of q-ROFSs. Bipolar Fuzzy Sets (BPSs) were introduced by Zhang [47] to manage uncertainties effectively. Equation (A7) demonstrates the details where the satisfaction degree is given as ${\mu_B}^+$ and satisfaction of the same element is shown by ${\mu_B}^-$. BPSs are integrated with other fuzzy sets in Equations (A8)–(A13). A comparison of fuzzy sets is found on [48].

Equations (A14)–(A17) include the calculations of bipolar q-ROFSs. Defuzzification is performed with Equations (A18)–(A20). The degrees are computed with the golden ratio (φ) in the analysis. Large and small quantities are indicated by a and b, whereas $(\mu_{G_{B_Q}},\ n_{G_{B_Q}})$ refers to new degrees [49]. Equations (A21)–(A23) include the details. The integration of the golden ratio with bipolar q-ROFSs is explained in Equations (A24)–(A26). The golden ratio is defined as the division of extreme and mean ratios in a straight line. In this context, a coefficient is created between the last and subsequent numbers. With the help of considering this ratio, a more realistic classification can be made.

3.2. M-SWARA Method with Bipolar q-ROFSs

Keršuliene et al. [50] generated SWARA intending to weight the items. In other words, the significance of the different criteria can be identified by considering this technique. In this study, significant improvements are made to this method, and a new technique is created called M-SWARA. As a result, a causal relationship can be made among the variables in addition to calculating the weights. Regarding the classical SWARA, the relative effectiveness of only one variable can be examined. However, concerning M-SWARA, the relationships of the variables can be considered with each other in an integrated manner. In the first stage of M-SWARA, the experts' evaluations are obtained. After that, these evaluations are converted into linguistic variables. With this method, each factor can be compared. Equation (A27) is used to create a relation matrix. In other words, the relation matrix includes comparative linguistic values between the items. The values of k_j (coefficient value), q_j (recalculated weight), s_j (comparative importance rate), and w_j (weights of the criteria) are calculated in Equations (A28)–(A30). These values are taken into consideration to create a stable matrix. Stable values are identified by transposing and limiting the matrix with the power of "2t + 1". Finally, considering the stable matrix, the weights of the items are computed.

3.3. ELECTRE with Bipolar q-ROFSs

Benayoun et al. [51] introduced ELECTRE with the help of binary superiority comparisons in alternative ranking. Hence, ELECTRE methodology is considered for ranking different alternatives based on their significance. An alternative selection is a critical issue in many subjects. The main reason is that by identifying an essential alternative, the companies or legal authorities can generate optimal strategies to achieve cost-effectiveness in this process. Similar to M-SWARA, in ELECTRE methodology, the experts' evaluations are obtained and converted into linguistic variables. With the help of these evaluations, average values are calculated. These values are considered for the calculation of score function and normalization values. As a result, a weighted decision matrix can be created. Concordance (CCD) and discordance (DCD) intervals are used in this process. Bipolar q-ROFSs are adopted with ELECTRE in this study. The decision matrix is created as in Equation (A31). Normalization is made by Equation (A32). The items are weighted in Equation (A33). CCD and DCD interval matrixes are created by Equations (A34)–(A39). The concordance E, discordance F, and aggregated G index matrixes are constructed with Equations (A40)–(A47). The sets of concordance, discordance, and aggregated index matrixes are given with e_{ab}, f_{ab}, g_{ab}. Furthermore, $\overline{c}$ and $\overline{d}$ refer to the critical values, whereas c_a, d_a, o_a represent the superior, inferior, and overall values. For ranking the alternatives, Equations (A48)–(A50) are taken into consideration.

3.4. Imputation of Expert Evaluations with Collaborative Filtering

The evaluations of the experts are mainly considered in decision-making models. Within this context, the main problem is the lack of knowledge of experts on a subject. The missing evaluations create a barrier to making an effective evaluation. Another problem in this process is that the experts can make evaluations without sufficient information about an issue. This situation has a negative influence on the appropriateness of the findings. For this purpose, collaborative filtering is considered to evaluate the users' tendencies. The predictions are made using similarity degrees between the users and factors [52]. Accordingly, the missing evaluations can be imputed using the expert–expert similarity and prediction indices of the collaborative filtering system. Equations (A51) and (A52) include the details of this approach. In these equations, $sim\ (u,v)$ represents the similarity index among the experts u and v. Furthermore, $r_{u,i}$ and $r_{v,i}$ show the rating degrees, whereas $\overline{r_u}$ and $\overline{r_v}$ demonstrate the averaged value. In addition, $p_{u,i}$ explains the prediction index.

3.5. Proposed Model

A model is generated in this study for evaluating the competencies of the knowledge economy by considering collaborative filtering and bipolar q-ROFSs with the golden ratio. The proposed model consists of three different phases. The first phase includes imputing the missing expert decisions for the balanced-scorecard-based evaluation of knowledge-oriented competencies. The second phase is related to weighting the balanced scorecard perspectives of distributed energy investments. The final phase focuses on ranking the balanced-scorecard-based evaluation of knowledge-oriented competencies for the distributed energy investments of emerging economies.

The focus is on emerging economies since those economies are the emerging giants of global demand and some of the primary energy producers. Energy consumption in these countries is generally low (per capita) but expanding economies and rising incomes create a vast potential for future growth [53]. In addition, the recent COVID-19 pandemic places additional pressure on these economies, and energy investments are even more difficult. Moreover, emerging economies are vulnerable to climate change due to a lack of resources to prevent or respond to its impact. At the same time, a dependable and affordable energy supply is crucial to their socioeconomic development [54].

Multi-criteria decision-making methods are considered to reach the appropriate decision in uncertain situations. However, the decision-making processes have started to become quite complex, and this situation has increased uncertainties in the process. Therefore, it has become difficult to reach a conclusion using only one technique [55]. In this context, it is aimed to achieve more effective results by using different techniques simultaneously. In addition, these approaches are also used with fuzzy numbers [56]. Thus, it is possible to make more effective decisions by minimizing uncertainties.

The proposed model has some essential superiorities. A new model is created with the name of M-SWARA by improving the classical SWARA. Hence, the causal directions can also be evaluated. Moreover, the degrees in bipolar q-ROFSs are computed by using the golden ratio, and this situation has an increasing impact on the model's originality. Additionally, with the help of collaborative filtering, the tendency of the users can be evaluated so that the experts' preferences can be predicted. Bipolar fuzzy sets also provide advantages, such as considering more comprehensive data sets. Therefore, the effectiveness of the model can be improved. ELECTRE methodology also has some superiorities, such as avoiding the compensation between criteria and the normalization process. The validity of the results can also be checked with the help of using both PFSs and IFSs in addition to q-ROFSs.

4. Analysis

This study aims to identify significant knowledge-oriented competencies of distributed energy investments. For this purpose, a unique decision-making model is generated with three stages. Firstly, collaborative filtering is adapted to the decision-making methodology to input the incomplete evaluations of the decision-makers. Secondly, the extension of SWARA entitled M-SWARA with bipolar q-ROFSs and the golden ratio is applied to figure out the impact-relation directions and the criteria weights. In this context, the perspectives of the balanced scorecard are taken into consideration. Thirdly, the extension of ELECTRE entitled golden ratio bipolar q-ROF ELECTRE is used to generate the possible directions among the competencies of knowledge-oriented distributed energy investments. The details of the proposed model are indicated in Figure 1.

The criteria are selected with a balanced scorecard approach, as in Table 1.

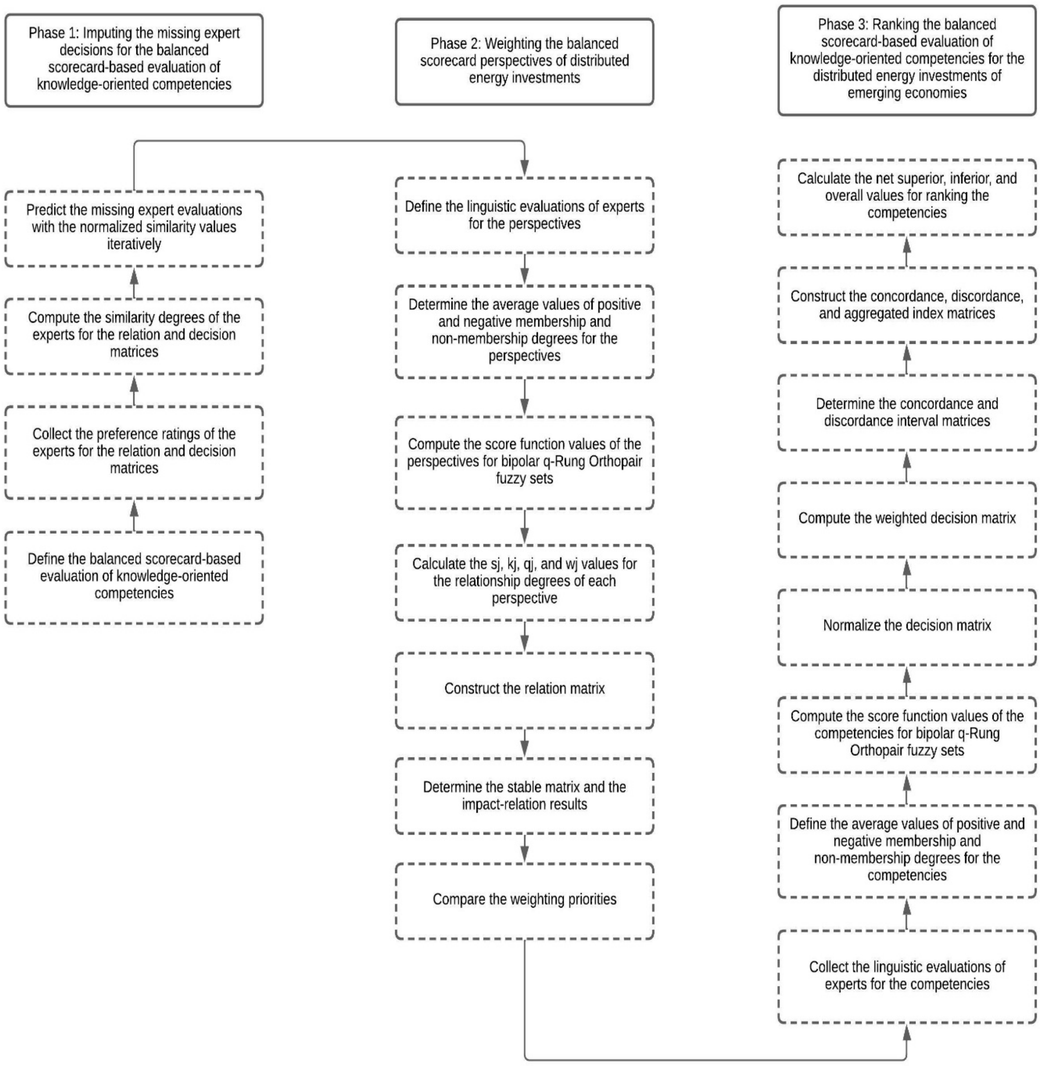

Figure 1. Flowchart.

Table 1. Balanced scorecard perspectives for distributed energy investments.

Perspectives	References
Finance (FNC)	[28,57]
Learning and Growth (LWT)	[32,58]
Customer (CTM)	[18,40]
Internal Process (IRS)	[29,59]

The balanced scorecard technique focused on both financial and non-financial issues. This situation provides a broader view while making an analysis [60]. Concerning the dimensions of finance, the projects' profitability is considered. In this context, the importance of cost-effectiveness is highlighted. Additionally, learning and growth provide information about the research and development activities to result in more effective distributed energy technologies. Furthermore, customer expectations should be considered for the sustainability of these investments. Finally, the internal process refers to organizational effectiveness. Table 2 provides information about the selected knowledge-oriented competencies for emerging economies.

Table 2. Selected knowledge-oriented competencies for emerging economies.

Competencies	References
Skilled Workforce (SLF)	[13,61]
Innovation Potential (ITT)	[19,62]
Regulations (RTS)	[63,64]
Information and Communication Technology (IMH)	[65,66]

A skilled workforce defines the qualified employee of the companies who can contribute to the performance of the projects. In addition, innovation potential refers to the capacity of the companies to make comprehensive research and development activities for technological improvement. Regulations refer to the rules created by legal authorities. These results can have a positive or negative influence on increasing knowledge-oriented competencies. The information and communication technologies of the companies can be helpful for effective cost management in this process. Table A1 in the appendix includes the scales and degrees used in this process, in which positive and negative degrees refer to PIE and NIE. Table A1 indicates that five different scales are considered to evaluate perspectives and competencies. In making calculations with the help of q-ROFSs, there is a need for positive and negative degrees. Equations (A5) and (A6) are used in this context to compute them. In this framework, the values in Table A3 are considered for the conversion of scales to degrees. The preference ratings of the experts are given in Table A2. In this table, the expression "n/a" refers to missing information due to the experts' lack of information about a subject. Table A3 demonstrates the preference ratings of the experts for the decision matrix of the competencies.

Six experts are appointed to evaluate the relation among the perspectives and decision matrix of the competencies of knowledge-oriented distributed energy investments concerning the balanced scorecard perspectives. The expert team comprises people with a minimum of 21 years of experience in distributed energy projects. Four of these people work as top managers, whereas two are academicians regarding this issue. The missing evaluations are completed by using collaborative filtering iteratively. The preference numbers from one to five are used for evaluating the decision makers, as seen in Table A1 (in the Appendix B). The similarity degrees of the experts for the perspectives and competencies are given in Tables A4 and A5.

Missing values are computed by considering the prediction index. For the first iteration, the highest value of normalized similarity degrees for each expert is selected for the similarity index value of the prediction. If the missing values are not completed in the first iteration, the second iteration is applied to complete the incomplete values. For the second iteration, the second highest value of normalized similarity degrees is selected for the similarity index value of prediction. If the missing expert evaluations are still available, the third iteration is applied with the highest third value among the normalized similarity degrees for each expert. Tables A6 and A7 refer to the completed expert evaluations for the perspectives and competencies, whereas ION refers to the iteration.

The second phase of the proposed model is related to weighting the balanced scorecard perspectives of distributed energy investments. Linguistic evaluations are obtained as in Table A8. For this purpose, completed expert evaluations with preference numbers are converted into linguistic evaluations. Score functions are shown in Table A9, and these functions are taken into consideration for the defuzzification process. Table A10 includes sj, kj, qj, and wj values that represent the comparative importance rate, coefficient value, recalculated weight, and criteria weights, respectively. In this process, Equations (A28)–(A30) are taken into consideration.

The relation matrix is created as in Table A11. This matrix gives information about the comparative relations among the perspectives. A stable matrix is created in Table A12. Stable values are identified by transposing and limiting the matrix with the power of "2t + 1". These values are taken into consideration to calculate the weights of the criteria. Causal directions are indicated in Figure 2. In this study, some improvements are made to the SWARA method. As a result, a new technique can be created by the name of M-SWARA. The main contribution of this new method is that the causal relationship between the factors can be evaluated. This situation provides an opportunity to create an impact relation map between the items. This condition helps to create more appropriate strategies for the companies to improve distributed energy projects.

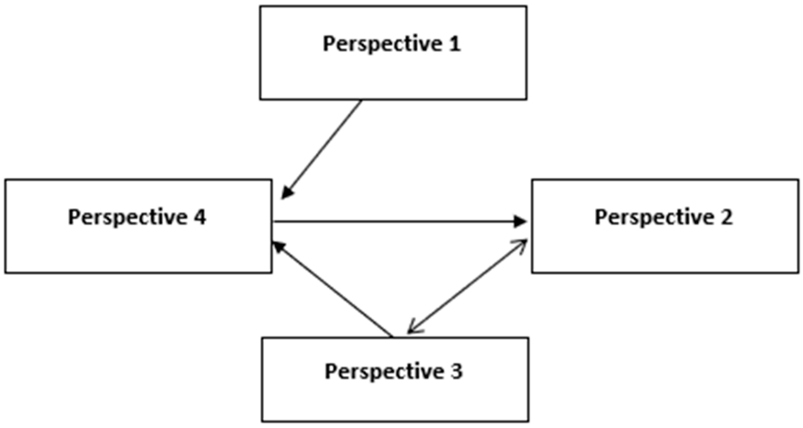

Figure 2. Impact-relation map for the perspectives.

The internal process is affected by finance and the customers. Moreover, there is a mutual relationship between learning and growth and the customers. Finally, learning and growth are influenced by an internal process. The comparative weights for Bipolar IFSs, Bipolar PFSs, and Bipolar q-ROFS are four for FNC, one for LWT, three for CTM, and two for IRS.

Learning and growth play a vital role in the performance of distributed energy investments. Furthermore, the internal process is also another essential perspective in this condition. The third phase of the proposed model includes ranking the balanced-scorecard-based evaluation of knowledge-oriented competencies for the distributed energy investments of emerging economies. The linguistic evaluations of experts for the competencies are collected in Table A13. In this table, the values of G, F, P, and B represent the scales for the competencies explained in Table A1. Average values are computed in Table A14. The score function values of the competencies are calculated in Table A15. Table A16 includes a normalized matrix. More effective evaluations can be made with the help of normalizing the values. In this framework, Equation (A32) is used. This matrix is weighted in Table A17 by considering Equation (A33).

In the analysis process with ELECTRE, a weighted matrix is considered to create interval matrixes. C and D matrixes are shown in Table A18 with the help of Equations (A34)–(A39). These matrixes are used to generate index matrixes. Table A19 includes E, F, and G matrixes. Within this context, Equations (A40)–(A47) are taken into consideration. These matrixes are mainly created to rank the alternatives. The impact-relation map of the competencies is illustrated in Figure 3. With the aim of improving distributed energy investment projects, knowledge-oriented competencies should be increased. In this process, identifying the key strategies plays a critical role. For this purpose, the cause-and-effect relationship between the items should be determined. This situation positively influences defining valid policies for the companies to increase these projects.

It is determined that information and communication technology influence the skilled workforce. In addition to this issue, to check the consistency of the findings, additional analyses are also performed using bipolar IFSs and PFSs. The comparative overall ranking results for the competencies are the following: for Bipolar q-ROF Multi SWARA-ELECTRE, and Bipolar PF Multi SWARA-ELECTRE is four for SLF, three for ITT, two for RTS, and one for IMH; and for the Bipolar IF Multi SWARA-ELECTRE the ranking is three for SLF, four for ITT, two for RTS and one for IMH.

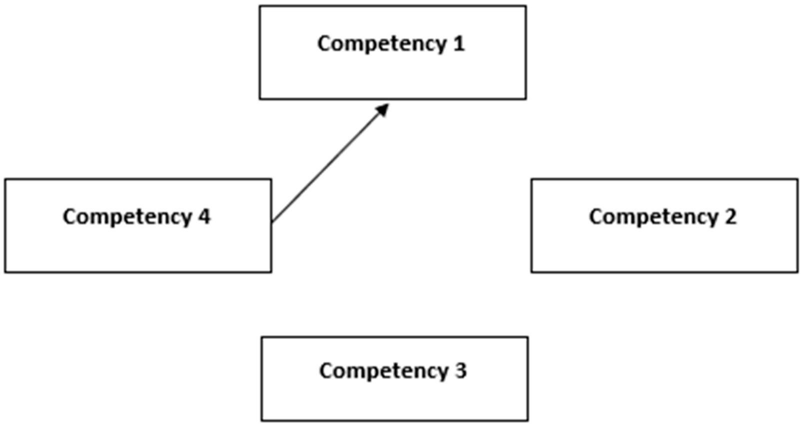

Figure 3. Impact-relation map for the competencies.

Information and communication technology has the most significant importance concerning the knowledge economy competency for the effectiveness of distributed energy projects. Regulations also play an essential role in these projects. Because the ranking results are the same for each fuzzy set, it is understood that the findings are valid and coherent.

5. Discussion

In distributed energy investment projects, energy production is at the point of consumption. Thanks to this situation, it is possible to reduce the cost of energy logistics. In addition, possible energy losses that may occur in this process can be minimized. However, these projects also have some difficulties. For example, excess energy is stored in these projects. These processes also increase the costs of distributed energy investment projects. Therefore, investors should prioritize technological developments. In recent years, severe technological developments have occurred regarding clean energy projects. Thanks to these developments, there have been significant reductions in the costs of these projects. Technological development is accelerating the transition to both wind and solar energy. Thanks to these developments, it will be possible to reduce high costs. Thus, both wind and solar energy will be able to compete better with fossil fuels. This situation will attract the attention of investors, and the transition to clean energy sources will gain momentum. Thus, it will be possible for distributed energy projects to develop more. Moreover, wind and solar energy investments involve complex processes. Qualified personnel are also needed to manage these processes effectively. Therefore, it is crucial to employ competent personnel in projects. Thanks to these personnel, possible problems that may occur will be solved efficiently and in a much shorter timeframe.

Technological developments also allow the application of new techniques discovered in this process. These new techniques reduce costs and increase efficiency in environmentally friendly energy projects. Therefore, it would be appropriate for investors who plan to invest in distributed energy projects to form a research and development team. Thanks to this team, new technologies will be followed instantly. In this way, companies will be able to gain a cost advantage. This will contribute to the development of energy production that does not harm the environment. Li et al. [67] studied distributed energy management systems and identified that research and development activities should be prioritized for performance improvement. Sarmiento-Vintimilla et al. [68] and Fonseca et al. [69] also determined that investors should prioritize technological developments to succeed in distributed energy investment projects. Some different conclusions were also reached in the literature regarding this issue. For instance, Donnellan and Kase [70] stated that customer expectations should be primarily satisfied in this framework.

Energy supply is a vital issue for countries. Since energy is used as an essential raw material in industrial production, countries must supply needed energy regardless of its price. The increase in energy prices for energy-importing countries adversely affects the current account balance. The problem of global warming also shows that the use of fossil fuels in energy production is hazardous. Therefore, countries should combat these problems by determining the right energy policies. In summary, while developing energy policy, priority should be given to increasing clean energy projects. Considering the analysis results obtained in this study, the private sector in countries must increase research and development studies on clean energy projects. States should encourage these efforts by providing the necessary support. Thus, the dependency on foreign energy production will decrease, and the adverse effects of the global warming problem will be minimized. Many researchers in the literature also emphasized this issue. For example, Sun et al. [71] and Li et al. [72] focused on ways to improve renewable energy investments. In these studies, many strategies were defined to reach this objective, such as creating hybrid renewable energy systems and identifying financial innovation priorities. Similarly, Dinçer et al. [73] also underlined the significance of microgeneration energy technologies in increasing clean energy investments.

The proposed model also has some superiorities when compared with the previously generated decision-making models. The main advantage of this proposed model is creating a new technique with the name of M-SWARA. Hence, the causal directions between the factors can also be identified in addition to calculating the weights of these items [74]. In some previous models where the classical SWARA technique was considered, the causality relationship between the criteria could not be identified [75,76]. Another significant superiority of this proposed model is that q-ROFSs are considered, and these sets use a more expansive space compared with IFSs and PFSs [77]. Because of this issue, it can be possible to have more accurate evaluations in comparison to the studies in which other fuzzy sets were considered [78,79].

6. Conclusions

Many factors can substantially impact the performance of distributed energy investments. For instance, effective financial analysis plays a crucial role in this regard. Similarly, customer expectations should also be satisfied so that the enterprises' products will be better preferred. Furthermore, businesses need to follow innovations carefully. Therefore, knowledge-oriented competencies should be provided for the success of these investments. Due to this issue, there is a need for a new study that will identify the most critical issues for distributed energy projects to have knowledge-oriented competencies. In order to make a priority analysis between the criteria, a complex methodological approach is needed to obtain obvious conclusions.

A new model is constructed to examine the competencies of the knowledge economy based on collaborative filtering and bipolar q-ROFSs with the golden ratio. Within this framework, this evaluation is made for emerging economies. The most important reason these country groups are preferred is that they make a significant investment to become a developed economy. In this process, there is a risk that the investments made will be uncontrolled. If these risks are not managed effectively, these countries will likely experience financial problems. Therefore, energy prices must be stable in emerging economies. These countries should refrain from relying on foreign countries for energy to achieve this goal. Therefore, the high performance of distributed energy investments is critical for these countries.

In the first stage, collaborative filtering is adapted to the decision-making methodology to input the incomplete evaluations of the decision-makers. The extension of SWARA entitled M-SWARA with bipolar q-ROFSs and the golden ratio is applied to figure out the impact-relation directions and the weights for the balanced scorecard perspectives with the imputed evaluations in the second stage. Finally, the possible directions among the competencies of knowledge-oriented distributed energy investments are created by the extension of ELECTRE entitled golden ratio bipolar q-ROF ELECTRE. It is determined that learning and growth are the most critical balanced scorecard perspectives. It is also concluded that information and communication technology is the most critical competency of the knowledge economy.

The main novelty of this study was the generation of a hybrid decision-making model with the imputation of missing expert evaluations and bipolar q-ROFSs. Another significant novelty was the identification of new fuzzy set scales by considering the theory of the golden ratio. An integrated evaluation approach was employed for emerging economies' knowledge-oriented distributed energy investments using the balanced scorecard dimensions. The analysis results pave the way for the investors to implement specific strategies to increase the performance of distributed energy projects with knowledge-oriented competencies. Making a general assessment of emerging economies can be accepted as a limitation of this manuscript. Hence, different countries or country groups can be considered for future studies, such as developed economies. Moreover, the proposed model can also be improved concerning future research direction. In this scope, picture fuzzy sets can be considered in the analysis process to manage uncertainties more appropriately. In addition, future research could extrapolate the analysis, taking into account recent developments regarding the role of fusion energy investments in the economies, which can be used to address long-term energy requirements and climate change, as well as issues regarding investment decisions between International Thermonuclear Experimental Reactor (ITER) members (of the Global North) and the non-ITER members (of the Global South) on fusion development. The proposed decision-making process developed in this article can guide emerging economies or other economies to be able to invest in fusion energy based on knowledge-oriented competencies. The proposed decision-making process can also guide other themes on ecosystemic decision analytics. It may have critical impacts and implications on theory, policy, practice, and politics in many contexts where complex, dynamic, over-constrained procedures are realized with multiple tradeoffs, such as health, education, defense, public finance, and research and development.

Author Contributions: Conceptualization, E.C. and P.K.; methodology, H.D. and S.Y.; software, H.D. and S.Y.; validation, H.D. and S.Y.; formal analysis, E.C. and P.K.; investigation, H.D. and S.Y.; resources, H.D. and S.Y.; data curation, H.D. and S.Y.; writing—original draft preparation, E.C. and P.K.; writing—review and editing, E.C. and P.K.; visualization, H.D. and S.Y.; supervision, E.C. and P.K.; project administration, E.C. and P.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

ELECTRE: The elimination and choice-translating reality is a method belonging to the family of outranking multicriteria decision-making techniques. It is used to select which alternative is preferable, indifferent, or incomparable. The method compares an alternative with another one under each criterion, taking purely ordinal scales into account. IFSs: The intuitionistic fuzzy set is a problem-solving method that incorporates the degree of hesitation called the hesitation margin. It has a powerful ability to represent and address the uncertainty of information. PFSs: The Pythagorean fuzzy set is a concept that generalizes intuitionistic fuzzy sets (IFSs) and is used in decision science because of its unique nature of indeterminacy. It is more capable of expressing and handling fuzzy information. q-ROFSs: The q-rung orthopair fuzzy sets are a generalization of PFSs. The rung q is the most significant feature of this notion. When the rung q increases, the orthopair adjusts in the boundary range, which is needed. Thus, the input range of q-ROFS is more flexible, resilient, and suitable than in approaches such as the IFSs and the PFSs. SWARA: The stepwise weight assessment ratio analysis is an efficient method for obtaining the subjective weights of criteria in multicriteria decision-making problems. In the first step, the method prioritizes the criteria by consulting experts, while in the second step, it weights the process. M-SWARA: The multi-stepwise weight assessment ratio analysis is an extension of the SWARA method.

Appendix A

$$I = \{\vartheta, \mu_I(\vartheta), n_I(\vartheta) / \vartheta \epsilon U\} \tag{A1}$$

$$0 \leq \mu_I(\vartheta) + n_I(\vartheta) \leq 1 \tag{A2}$$

$$P = \{\vartheta, \mu_P(\vartheta), n_P(\vartheta) / \vartheta \epsilon U\} \tag{A3}$$

$$0 \leq (\mu_P(\vartheta))^2 + (n_P(\vartheta))^2 \leq 1 \tag{A4}$$

$$Q = \{\langle \vartheta, \mu_Q(\vartheta), n_Q(\vartheta) \rangle / \vartheta \epsilon U\} \tag{A5}$$

$$0 \leq (\mu_Q(\vartheta))^q + (n_Q(\vartheta))^q \leq 1\,, \;\; q \geq 1 \tag{A6}$$

$$B = \{\langle \vartheta,\ \mu_B{}^+(\vartheta), \mu_B{}^-(\vartheta) \rangle / \vartheta \epsilon U\} \tag{A7}$$

$$B_I = \{\langle \vartheta,\ \mu_{B_I}{}^+(\vartheta), n_{B_I}{}^+(\vartheta), \mu_{B_I}{}^-(\vartheta), n_{B_I}{}^-(\vartheta) \rangle / \vartheta \epsilon U\} \tag{A8}$$

$$B_P = \{\langle \vartheta,\ \mu_{B_P}{}^+(\vartheta), n_{B_P}{}^+(\vartheta), \mu_{B_P}{}^-(\vartheta), n_{B_P}{}^-(\vartheta) \rangle / \vartheta \epsilon U\} \tag{A9}$$

$$B_Q = \left\{\langle \vartheta,\ \mu_{B_Q}{}^+(\vartheta), n_{B_Q}{}^+(\vartheta), \mu_{B_Q}{}^-(\vartheta), n_{B_Q}{}^-(\vartheta) \rangle / \vartheta \epsilon U\right\} \tag{A10}$$

$$0 \leq (\ \mu_{B_I}{}^+(\vartheta)) + (\ n_{B_I}{}^+(\vartheta))\ \leq 1\,, -1 \leq (\ \mu_{B_I}{}^-(\vartheta)) + (\ n_{B_I}{}^-(\vartheta))\ \leq 0 \tag{A11}$$

$$0 \leq (\ \mu_{B_P}{}^+(\vartheta))^2 + (\ n_{B_P}{}^+(\vartheta))^2 \leq 1,\ 0 \leq (\ \mu_{B_P}{}^-(\vartheta))^2 + (\ n_{B_P}{}^-(\vartheta))^2 \leq 1 \tag{A12}$$

$$0 \leq \left(\ \mu_{B_Q}{}^+(\vartheta)\right)^q + \left(\ n_{B_Q}{}^+(\vartheta)\right)^q \leq 1\,, -1 \leq \left(\ \mu_{B_Q}{}^-(\vartheta)\right)^q + \left(\ n_{B_Q}{}^-(\vartheta)\right)^q \leq 0 \tag{A13}$$

$$B_{Q1} = \left\{\langle \vartheta,\ \mu_{B_{Q1}}{}^+(\vartheta), n_{B_{Q1}}{}^+(\vartheta), \mu_{B_{Q1}}{}^-(\vartheta), n_{B_{Q1}}{}^-(\vartheta) \rangle / \vartheta \epsilon U\right\} \text{ and}$$
$$B_{Q2} = \left\{\langle \vartheta,\ \mu_{B_{Q2}}{}^+(\vartheta), n_{B_{Q2}}{}^+(\vartheta), \mu_{B_{Q2}}{}^-(\vartheta), n_{B_{Q2}}{}^-(\vartheta) \rangle / \vartheta \epsilon U\right\}$$

$$\begin{aligned} B_{Q1} \oplus B_{Q2} = \ & \Bigg(\bigg(\Big(\mu_{B_{Q1}}{}^+\Big)^q + \Big(\mu_{B_{Q2}}{}^+\Big)^q \\ & -\Big(\mu_{B_{Q1}}{}^+\Big)^q.\Big(\mu_{B_{Q2}}{}^+\Big)^q\bigg)^{\frac{1}{q}},\ \Big(n_{B_{Q1}}{}^+.\ n_{B_{Q2}}{}^+\Big), -\Big(\mu_{B_{Q1}}{}^-.\ \mu_{B_{Q2}}{}^-\Big), -\bigg(\Big(n_{B_{Q1}}{}^-\Big)^q \\ & +\Big(n_{B_{Q2}}{}^-\Big)^q - \Big(n_{B_{Q1}}{}^-\Big)^q.\Big(n_{B_{Q2}}{}^-\Big)^q\bigg)^{\frac{1}{q}}\Bigg) \end{aligned} \tag{A14}$$

$$\begin{aligned} B_{Q1} \otimes B_{Q2} = & \Bigg(\Big(\mu_{B_{Q_1}}{}^+ \cdot \mu_{B_{Q_2}}{}^+\Big), \bigg(\Big(n_{B_{Q_1}}{}^+\Big)^q + \Big(n_{B_{Q_2}}{}^+\Big)^q - \Big(n_{B_{Q_1}}{}^+\Big)^q \cdot \Big(n_{B_{Q_2}}{}^+\Big)^q\bigg)^{\frac{1}{q}}, -\bigg(\Big(\mu_{B_{Q_1}}{}^-\Big)^q \\ & +\Big(\mu_{B_{Q_2}}{}^-\Big)^q - \Big(\mu_{B_{Q_1}}{}^-\Big)^q \cdot \Big(\mu_{B_{Q_2}}{}^-\Big)^q\bigg)^{\frac{1}{q}}, -\Big(n_{B_{Q_1}} - .n_{B_{Q_2}}{}^-\Big)\Bigg) \end{aligned} \tag{A15}$$

$$\lambda B_{Q1} = \left(\left(1 - \left(1 - \left(\mu_{B_{Q1}}{}^+\right)^q\right)^\lambda\right)^{1/q},\ \left(n_{B_{Q1}}{}^+\right)^\lambda, -\left(-\mu_{B_{Q1}}{}^-\right)^\lambda, -\left(1 - \left(1 - \left(-n_{B_{Q1}}{}^-\right)^q\right)^\lambda\right)^{1/q}\right), \lambda > 0 \tag{A16}$$

$$B_{Q1}{}^\lambda = \left(\left(\mu_{B_{Q1}}{}^+\right)^\lambda,\ \left(1 - \left(1 - \left(n_{B_{Q1}}{}^+\right)^q\right)^\lambda\right)^{1/q}, -\left(1 - \left(1 - \left(-\mu_{B_{Q1}}{}^-\right)^q\right)^\lambda\right)^{\frac{1}{q}}, -\left(-n_{B_{Q1}}{}^-\right)^\lambda\right), \lambda > 0 \tag{A17}$$

$$S(\vartheta)_{B_I} = \left(\left(\mu_{B_I}{}^+(\vartheta)\right) - \left(n_{B_I}{}^+(\vartheta)\right)\right) - \left(\left(\mu_{B_I}{}^-(\vartheta)\right) - \left(n_{B_I}{}^-(\vartheta)\right)\right) \tag{A18}$$

$$S(\vartheta)_{B_P} = \left(\left(\mu_{B_P}{}^+(\vartheta)\right)^2 - \left(n_{B_P}{}^+(\vartheta)\right)^2\right) + \left(\left(\mu_{B_P}{}^-(\vartheta)\right)^2 - \left(n_{B_P}{}^-(\vartheta)\right)^2\right) \tag{A19}$$

$$S(\vartheta)_{B_Q} = \left(\left(\mu_{B_Q}{}^+(\vartheta)\right)^q - \left(n_{B_Q}{}^+(\vartheta)\right)^q\right) - \left(\left(\mu_{B_Q}{}^-(\vartheta)\right)^q - \left(n_{B_Q}{}^-(\vartheta)\right)^q\right) \tag{A20}$$

$$\varphi = \frac{a}{b} \tag{A21}$$

$$\varphi = \frac{1+\sqrt{5}}{2} = 1.618\ldots \tag{A22}$$

$$\varphi = \frac{\mu_{G_{B_Q}}}{n_{G_{B_Q}}} \tag{A23}$$

$$G_{B_Q} = \left\{ \langle \vartheta,\ \mu_{G_{B_Q}}{}^{+}(\vartheta), n_{G_{B_Q}}{}^{+}(\vartheta), \mu_{G_{B_Q}}{}^{-}(\vartheta), n_{G_{B_Q}}{}^{-}(\vartheta) \rangle / \vartheta \epsilon U \right\} \tag{A24}$$

$$0 \leq \left(\mu_{G_{B_Q}}{}^{+}(\vartheta) \right)^{q} + \left(n_{G_{B_Q}}{}^{+}(\vartheta) \right)^{q} \leq 1, -1 \leq \left(\mu_{G_{B_Q}}{}^{-}(\vartheta) \right)^{q} + \left(n_{G_{B_Q}}{}^{-}(\vartheta) \right)^{q} \leq 0 \tag{A25}$$

$$0 \leq \left(\mu_{G_{B_Q}}{}^{+}(\vartheta) \right)^{2q} + \left(n_{G_{B_Q}}{}^{+}(\vartheta) \right)^{2q} \leq 1,\ 0 \leq \left(\mu_{G_{B_Q}}{}^{-}(\vartheta) \right)^{2q} + \left(n_{G_{B_Q}}{}^{-}(\vartheta) \right)^{2q} \leq 1\ q \geq 1 \tag{A26}$$

$$Q_k = \begin{bmatrix} 0 & Q_{12} & \cdots & \cdots & Q_{1n} \\ Q_{21} & 0 & \cdots & \cdots & Q_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ Q_{n1} & Q_{n2} & \cdots & \cdots & 0 \end{bmatrix} \tag{A27}$$

$$k_j = \begin{cases} 1\ j = 1 \\ s_j + 1\ j > 1 \end{cases} \tag{A28}$$

$$q_j = \begin{cases} 1\ j = 1 \\ \frac{q_{j-1}}{k_j}\ j > 1 \end{cases} \tag{A29}$$

$$\begin{gathered} If s_{j-1} = s_j, q_{j-1} = q_j; If s_j = 0, k_{j-1} = k_j \\ w_j = \frac{q_j}{\sum_{k=1}^{n} q_k} \end{gathered} \tag{A30}$$

$$X_k = \begin{bmatrix} 0 & X_{12} & \cdots & \cdots & X_{1m} \\ X_{21} & 0 & \cdots & \cdots & X_{2m} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ X_{n1} & X_{n2} & \cdots & \cdots & 0 \end{bmatrix} \tag{A31}$$

$$r_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{m} X_{ij}^2}}. \tag{A32}$$

$$v_{ij} = w_{ij} \times r_{ij} \tag{A33}$$

$$C = \begin{bmatrix} - & c_{12} & \cdots & \cdots & c_{1n} \\ c_{21} & - & \cdots & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ c_{n1} & c_{n2} & \cdots & \cdots & - \end{bmatrix} \tag{A34}$$

$$D = \begin{bmatrix} - & d_{12} & \cdots & \cdots & d_{1n} \\ d_{21} & - & \cdots & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \cdots & \cdots & - \end{bmatrix} \tag{A35}$$

$$c_{ab} = \left\{ j \middle| v_{aj} \geq v_{bj} \right\} \tag{A36}$$

$$d_{ab} = \left\{ j \middle| v_{aj} < v_{bj} \right\} \tag{A37}$$

$$c_{ab} = \sum_{j \in c_{ab}} w_j \tag{A38}$$

$$d_{ab} = \frac{\max_{j \in d_{ab}} \left| v_{aj} - v_{bj} \right|}{\max_j \left| v_{mj} - v_{nj} \right|} \tag{A39}$$

$$E = \begin{bmatrix} - & e_{12} & \cdots & \cdots & e_{1n} \\ e_{21} & - & \cdots & \cdots & e_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ e_{n1} & e_{n2} & \cdots & \cdots & - \end{bmatrix} \tag{A40}$$

$$F = \begin{bmatrix} - & f_{12} & \cdots & \cdots & f_{1n} \\ f_{21} & - & \cdots & \cdots & f_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ f_{n1} & f_{n2} & \cdots & \cdots & - \end{bmatrix} \tag{A41}$$

$$G = \begin{bmatrix} - & g_{12} & \cdots & \cdots & g_{1n} \\ g_{21} & - & \cdots & \cdots & g_{2n} \\ \vdots & \vdots & \ddots & \cdots & \cdots \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ g_{n1} & g_{n2} & \cdots & \cdots & - \end{bmatrix} \tag{A42}$$

$$\begin{cases} e_{ab} = 1 \; if \; c_{ab} \geq \overline{c} \\ e_{ab} = 0 \; if \; c_{ab} < \overline{c} \end{cases} \tag{A43}$$

$$\overline{c} = \sum_{a=1}^{n} \sum_{b}^{n} c_{ab} / n(n-1) \tag{A44}$$

$$\begin{cases} f_{ab} = 1 \; if \; d_{ab} \leq \overline{d} \\ f_{ab} = 0 \; if \; d_{ab} > \overline{d} \end{cases} \tag{A45}$$

$$\overline{d} = \sum_{a=1}^{n} \sum_{b}^{n} d_{ab} / n(n-1) \tag{A46}$$

$$g_{ab} = e_{ab} \times f_{ab} \tag{A47}$$

$$c_a = \sum_{b=1}^{n} c_{ab} - \sum_{b=1}^{n} c_{ba} \tag{A48}$$

$$d_a = \sum_{b=1}^{n} d_{ab} - \sum_{b=1}^{n} d_{ba} \tag{A49}$$

$$o_a = c_a - d_a \tag{A50}$$

$$sim(u,v) = \frac{\sum_{i \in I} (r_{u,i} - \overline{r_u})(r_{v,i} - \overline{r_v})}{\sqrt{\sum_{i \in I} (r_{u,i} - \overline{r_u})^2} \sqrt{\sum_{i \in I} (r_{v,i} - \overline{r_v})^2}} \tag{A51}$$

$$p_{u,i} = \frac{\sum_{j \in S} sim(u,v) r_{u,j}}{\sum_{j \in S} |sim(u,v)|} \tag{A52}$$

Appendix B

Table A1. Scales and Degrees.

Scales			PIE		NIE	
Perspectives	**Competencies**	**Preference Numbers**	**MMP**	**NNP**	**MMP**	**NNP**
No (n)	Weakest (w)	1	0.40	0.25	−0.60	−0.37
Some (s)	Poor (p)	2	0.45	0.28	−0.55	−0.34
Medium (m)	Fair (f)	3	0.50	0.31	−0.50	−0.31
High (h)	Good (g)	4	0.55	0.34	−0.45	−0.28
Very High (vh)	Best (b)	5	0.60	0.37	−0.40	−0.25

Table A2. The preference ratings of the experts for the relation matrix of perspectives.

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
FNC-LWT	n/a	n/a	3	4	3	4
FNC-CTM	n/a	5	3	4	3	n/a
FNC-IRS	4	n/a	5	n/a	n/a	5
LWT-FNC	4	4	n/a	5	2	n/a
LWT-CTM	5	4	n/a	5	n/a	n/a
LWT-IRS	3	n/a	n/a	n/a	2	5
CTM-FNC	3	n/a	4	n/a	n/a	n/a
CTM-LWT	n/a	4	4	3	4	3
CTM-IRS	5	n/a	n/a	3	n/a	3
IRS-FNC	5	4	4	n/a	n/a	n/a
IRS-LWT	5	5	n/a	5	4	4
IRS-CTM	n/a	n/a	5	5	n/a	2

Note: n/a” refers to missing information.

Table A3. The preference ratings of the experts for the decision matrix of the competencies.

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
FNC-SLF	4	2	5	n/a	2	n/a
FNC-ITT	3	5	4	n/a	n/a	5
FNC-RTS	n/a	n/a	4	4	5	5
FNC-IMH	n/a	5	4	5	4	n/a
LWT-SLF	3	n/a	5	5	4	n/a
LWT-ITT	2	3	n/a	n/a	5	4
LWT-RTS	n/a	3	3	4	5	n/a
LWT-IMH	n/a	n/a	3	5	5	n/a
CTM-SLF	4	3	n/a	4	n/a	3
CTM-ITT	n/a	n/a	n/a	5	4	4
CTM-RTS	5	3	3	3	n/a	n/a
CTM-IMH	n/a	n/a	n/a	4	4	5
IRS-SLF	4	n/a	4	3	4	n/a
IRS-ITT	5	3	3	n/a	4	n/a
IRS-RTS	5	n/a	4	n/a	5	5
IRS-IMH	n/a	3	5	4	2	n/a

Note: n/a” refers to missing information.

Table A4. Similarity index matrix of the experts for the perspectives.

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Expert 1	1.00	0.03	−0.08	0.00	0.48	−0.34
Expert 2	0.03	1.00	−0.28	0.09	0.29	0.10
Expert 3	−0.08	−0.28	1.00	0.23	0.04	−0.23
Expert 4	−0.00	0.09	0.23	1.00	−0.27	0.15
Expert 5	−0.48	0.29	0.04	−0.27	1.00	−0.35
Expert 6	−0.34	0.10	−0.23	0.15	−0.35	1.00

Table A5. Similarity index matrix of the experts for the competencies.

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
Expert 1	1.00	−0.21	−0.36	−0.31	−0.09	0.14
Expert 2	−0.21	1.00	−0.08	0.29	0.27	0.29
Expert 3	−0.36	−0.08	1.00	0.18	−0.64	0.03
Expert 4	−0.31	0.29	0.18	1.00	0.08	−0.07
Expert 5	−0.09	0.27	−0.64	0.08	1.00	0.09
Expert 6	0.14	0.29	0.03	−0.07	0.09	1.00

Table A6. Completed expert evaluations for the perspectives.

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
FNC-LWT	3 (ION 1)	3 (ION 1)	3	4	3	4
FNC-CTM	3 (ION 1)	5	3	4	3	4 (ION 1)
FNC-IRS	4	5 (ION 2)	5	5 (ION 1)	4 (ION 1)	5
LWT-FNC	4	4	5 (ION 1)	5	2	5 (ION 1)
LWT-CTM	5	4	5 (ION 1)	5	5 (ION 1)	5 (ION 1)
LWT-IRS	3	2 (ION 1)	2 (ION 2)	5 (ION 2)	2	5
CTM-FNC	3	3 (ION 4)	4	4 (ION 1)	3 (ION 1)	4 (ION 3)
CTM-LWT	4 (ION 1)	4	4	3	4	3
CTM-IRS	5	3 (ION 2)	3 (ION 1)	3	5 (ION 1)	3
IRS-FNC	5	4	4	4 (ION 1)	5 (ION 1)	4 (ION 2)
IRS-LWT	5	5	5 (ION 1)	5	4	4
IRS-CTM	5 (ION 3)	2 (ION 2)	5	5	5 (ION 3)	2

Table A7. Completed expert evaluations for the competencies.

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
FNC-SLF	4	2	5	2 (ION 1)	2	2 (ION 1)
FNC-ITT	3	5	4	5 (ION 1)	5 (ION 1)	5
FNC-RTS	5 (ION 1)	4 (ION 1)	4	4	5	5
FNC-IMH	4 (ION 2)	5	4	5	4	5 (ION 1)
LWT-SLF	3	5 (ION 1)	5	5	4	3 (ION 2)
LWT-ITT	2	3	4 (ION 2)	3 (ION 1)	5	4
LWT-RTS	5 (ION 2)	3	3	4	5	3 (ION 1)
LWT-IMH	5 (ION 2)	5 (ION 1)	3	5	5	5 (ION 3)
CTM-SLF	4	3	4 (ION 1)	4	3 (ION 1)	3
CTM-ITT	4 (ION 1)	5 (ION 1)	5 (ION 1)	5	4	4
CTM-RTS	5	3	3	3	3 (ION 1)	3 (ION 1)
CTM-IMH	5 (ION 1)	4 (ION 1)	4 (ION 1)	4	4	5
IRS-SLF	4	3 (ION 1)	4	3	4	4 (ION 2)
IRS-ITT++	5	3	3	3 (ION 1)	4	3 (ION 1)
IRS-RTS	5	5 (ION 2)	4	4 (ION 2)	5	5
IRS-IMH	2 (ION 2)	3	5	4	2	3 (ION 1)

Table A8. Linguistic evaluations of experts for the perspectives.

	Expert 1				Expert 2			
	FNC	**LWT**	**CTM**	**IRS**	**FNC**	**LWT**	**CTM**	**IRS**
FNC		M	M	H		M	VH	VH
LWT	H		VH	M	H		H	S
CTM	M	H		VH	M	H		M
IRS	VH	VH	VH		H	VH	S	

Table A8. *Cont.*

	Expert 3				Expert 4			
	FNC	**LWT**	**CTM**	**IRS**	**FNC**	**LWT**	**CTM**	**IRS**
FNC		M	M	VH		H	H	VH
LWT	VH		VH	S	VH		VH	VH
CTM	H	H		M	H	M		M
IRS	H	VH	VH		H	VH	VH	
	Expert 5				**Expert 6**			
	FNC	**LWT**	**CTM**	**IRS**	**FNC**	**LWT**	**CTM**	**IRS**
FNC		M	M	H		H	H	VH
LWT	S		VH	S	VH		VH	VH
CTM	M	H		VH	H	M		M
IRS	VH	H	VH		H	H	S	

Table A9. Score function values of the perspectives.

	FNC	LWT	CTM	IRS
FNC	0.000	0.192	0.194	0.207
LWT	0.199	0.000	0.210	0.191
CTM	0.192	0.194	0.000	0.194
IRS	0.201	0.207	0.197	0.000

Table A10. Sj, kj, qj, and wj values for the relationship degrees of each perspective.

FNC	Sj	Kj	qj	wj	LWT	Sj	kj	Qj	Wj
IRS	0.207	1.000	1.000	0.394	CTM	0.210	1.000	1.000	0.395
CTM	0.194	1.194	0.838	0.330	FNC	0.199	1.199	0.834	0.329
LWT	0.192	1.192	0.703	0.277	IRS	0.191	1.191	0.700	0.276
CTM	**Sj**	**kj**	**qj**	**wj**	**IRS**	**Sj**	**kj**	**Qj**	**Wj**
LWT	0.194	1.000	1.000	0.352	LWT	0.207	1.000	1.000	0.396
IRS	0.194	1.000	1.000	0.352	FNC	0.201	1.201	0.833	0.329
FNC	0.192	1.192	0.839	0.295	CTM	0.197	1.197	0.696	0.275

Table A11. Relation Matrix with the values of wj.

	FNC	LWT	CTM	IRS
FNC		0.277	0.330	0.394
LWT	0.329		0.395	0.276
CTM	0.295	0.352		0.352
IRS	0.329	0.396	0.275	

Table A12. Stable Matrix.

	FNC	LWT	CTM	IRS
FNC	0.241	0.241	0.241	0.241
LWT	0.255	0.255	0.255	0.255
CTM	0.250	0.250	0.250	0.250
IRS	0.254	0.253	0.254	0.254

Table A13. Linguistic evaluations of experts for the positive and negative degrees of competencies.

	Expert 1				Expert 2			
	SLF	**ITT**	**RTS**	**IMH**	**SLF**	**ITT**	**RTS**	**IMH**
FNC	G	F	G	G	P	B	F	F
LWT	F	P	G	B	B	F	B	F
CTM	B	B	B	B	G	F	F	B
IRS	G	B	B	P	B	B	G	F
	Expert 3				**Expert 4**			
	SLF	**ITT**	**RTS**	**IMH**	**SLF**	**ITT**	**RTS**	**IMH**
FNC	B	B	G	G	P	B	G	F
LWT	G	G	B	F	B	F	B	F
CTM	G	F	F	G	G	G	F	G
IRS	G	F	G	B	B	B	G	G
	Expert 5				**Expert 6**			
	SLF	**ITT**	**RTS**	**IMH**	**SLF**	**ITT**	**RTS**	**IMH**
FNC	P	G	F	G	P	F	F	G
LWT	B	B	G	G	B	G	G	F
CTM	B	B	F	B	B	F	F	B
IRS	G	B	G	P	B	B	B	F

Table A14. Average values for the competencies.

	SLF				ITT				RTS				IMH			
	PIE		**NIE**		**PIE**		**NIE**		**PIE**		**NIE**		**PIE**		**NIE**	
	μ	**n**	**μ**	**n**	**μ**	**n**	**μ**	**n**	**μ**	**n**	**μ**	**n**	**μ**	**n**	**μ**	**n**
FNC	0.49	0.30	−0.51	−0.31	0.56	0.35	−0.44	−0.27	0.53	0.32	−0.48	−0.29	0.53	0.33	−0.47	−0.29
LWT	0.58	0.36	−0.43	−0.26	0.53	0.32	−0.48	−0.29	0.58	0.36	−0.43	−0.26	0.53	0.32	−0.48	−0.29
CTM	0.58	0.36	−0.43	−0.26	0.54	0.33	−0.46	−0.28	0.52	0.32	−0.48	−0.30	0.58	0.36	−0.42	−0.26
IRS	0.58	0.36	−0.43	−0.26	0.58	0.36	−0.42	−0.26	0.57	0.35	−0.43	−0.27	0.51	0.31	−0.49	−0.30

Table A15. Score function values of the competencies.

	SLF	**ITT**	**RTS**	**IMH**
FNC	0.191	0.199	0.192	0.194
LWT	0.204	0.192	0.204	0.192
CTM	0.204	0.195	0.192	0.207
IRS	0.204	0.207	0.201	0.191

Table A16. Normalized matrix.

	SLF	**ITT**	**RTS**	**IMH**
FNC	0.476	0.501	0.488	0.493
LWT	0.508	0.485	0.517	0.491
CTM	0.508	0.491	0.486	0.528
IRS	0.508	0.522	0.510	0.487

Table A17. Weighted matrix.

	SLF	**ITT**	**RTS**	**IMH**
FNC	0.115	0.128	0.122	0.125
LWT	0.123	0.124	0.129	0.124
CTM	0.123	0.125	0.121	0.134
IRS	0.123	0.133	0.127	0.124

Table A18. C and D matrixes.

	C				D			
	SLF	**ITT**	**RTS**	**IMH**	**SLF**	**ITT**	**RTS**	**IMH**
SLF	0.000	0.509	0.505	0.254	0.000	1.000	1.000	1.000
ITT	0.491	0.000	0.491	0.745	0.535	0.000	1.000	1.000
RTS	0.495	0.750	0.000	0.495	0.284	0.829	0.000	0.754
IMH	0.746	0.497	0.746	0.000	0.202	0.184	1.000	0.000

Table A19. E, F and G matrixes.

	E				F				G			
	SLF	**ITT**	**RTS**	**IMH**	**SLF**	**ITT**	**RTS**	**IMH**	**SLF**	**ITT**	**RTS**	**IMH**
SLF	0	0	0	0	1	0	0	0	0	0	0	0
ITT	0	0	0	1	1	1	0	0	0	0	0	0
RTS	0	1	0	0	1	0	1	0	0	0	0	0
IMH	1	0	1	0	1	1	0	1	1	0	0	0

References

1. Carayannis, E.G.; Draper, J.; Iftimie, I.A. Nuclear Fusion Diffusion: Theory, Policy, Practice, and Politics Perspectives. *IEEE Trans. Eng. Manag.* **2022**, *69*, 1237–1251. [CrossRef]
2. Carlucci, D.; Renna, P.; Materi, S. A Job-Shop Scheduling Decision-Making Model for Sustainable Production Planning With Power Constraint. *IEEE Trans. Eng. Manag.* **2021**, *14*, 6264. [CrossRef]
3. Dokas, I.; Panagiotidis, M.; Papadamou, S.; Spyromitros, E. The Determinants of Energy and Electricity Consumption in Developed and Developing Countries: International Evidence. *Energies* **2022**, *15*, 2558. [CrossRef]
4. Zhu, X.; Wang, J.; Coit, D.W. Joint Optimization of Spare Part Supply and Opportunistic Condition-Based Maintenance for Onshore Wind Farms Considering Maintenance Route. *IEEE Trans. Eng.Manag.* **2022**. [CrossRef]
5. Song, C.H. Exploring and Predicting the Knowledge Development in the Field of Energy Storage: Evidence from the Emerging Startup Landscape. *Energies* **2021**, *14*, 5822. [CrossRef]
6. Katsampoxakis, I.; Christopoulos, A.; Kalantonis, P.; Nastas, V. Crude Oil Price Shocks and European Stock Markets during the COVID-19 Period. *Energies* **2022**, *15*, 4090. [CrossRef]
7. Wang, C.N.; Nhieu, N.L.; Dao, T.H.; Huang, C.C. Simulation-Based Optimized Weighting TODIM Decision-Making Approach for National Oil Company Global Benchmarking. *IEEE Trans. Eng. Manag.* **2022**. [CrossRef]
8. Zakernezhad, H.; Nazar, M.S.; Shafie-khah, M.; Catalão, J.P. Optimal resilient operation of multi-carrier energy systems in electricity markets considering distributed energy resource aggregators. *Appl. Energy* **2021**, *299*, 117271. [CrossRef]
9. Skačkauskienė, I.; Smirnova, J. Review of Possibilities for Evaluating the Performance of an Organization in the Aspect of Greenness. *Energies* **2022**, *15*, 6947. [CrossRef]
10. Fonseca, J.D.; Commenge, J.M.; Camargo, M.; Falk, L.; Gil, I.D. Multi-criteria optimization for the design and operation of distributed energy systems considering sustainability dimensions. *Energy* **2021**, *214*, 118989. [CrossRef]
11. Li, S.; Gu, C. Multi-Objective Bi-Directional V2G Behavior Optimization and Strategy Deployment. In *Automated and Electric Vehicle: Design, Informatics and Sustainability*; Springer: Singapore, 2023; pp. 135–152.
12. Gilev, B.; Andreev, M.; Hinov, N.; Angelov, G. Modeling and Simulation of a Low-Cost Fast Charging Station Based on a Micro Gas Turbine and a Supercapacitor. *Energies* **2022**, *15*, 8020. [CrossRef]
13. Mortezapour, V.; Golshannavaz, S.; Pouresmaeil, E.; Yazdaninejadi, A. A new hybrid control technique for operation of DC microgrid under islanded operating mode. *Prot. Control. Mod. Power Syst.* **2022**, *7*, 42. [CrossRef]
14. Carayannis, E.G.; Grigoroudis, E.; Campbell, D.F.J.; Meissner, D.; Stamati, D. The ecosystem as helix: An exploratory theory-building study of regional coopetitive entrepreneurial ecosystems as Quadruple/Quintuple Helix Innovation Models. *RD Manag.* **2018**, *48*, 148–162. [CrossRef]
15. Gadde, P.H.; Gani, M.B.; Enslin, J.H. An AC/DC Hybrid Campus Microgrid: Modelling, Control and Financial Analysis. In Proceedings of the 2021 IEEE 12th International Symposium on Power Electronics for Distributed Generation Systems (PEDG), Chicago, IL, USA, 28 June–1 July 2021; pp. 1–7.
16. Heinrich, C.; Ziras, C.; Jensen, T.V.; Bindner, H.W.; Kazempour, J. A local flexibility market mechanism with capacity limitation services. *Energy Policy* **2021**, *156*, 112335. [CrossRef]
17. Zhao, D.; Xia, Z.; Guo, M.; He, Q.; Xu, Q.; Li, X.; Ni, M. Capacity optimization and energy dispatch strategy of hybrid energy storage system based on proton exchange membrane electrolyzer cell. *Energy Convers. Manag.* **2022**, *272*, 116366. [CrossRef]
18. Mukhtarov, S.; Yüksel, S.; Dinçer, H. The impact of financial development on renewable energy consumption: Evidence from Turkey. *Renew. Energy* **2022**, *187*, 169–176. [CrossRef]

19. Meléndez-González, C.R.; Colón-González, A.M.; Ortiz-Rodríguez, A.G.; López-Silva, M.A.; Ortiz-Rivera, E. Training a New Generation of Solar Developers with the Latest Tools and Practices Provided by DOE's Professionals: The UPRM Experience. In Proceedings of the 2021 IEEE Frontiers in Education Conference (FIE), Lincoln, NE, USA, 13–16 October 2021; pp. 1–8.
20. Mahani, K.; Jamali, M.A.; Nazemi, S.D.; Jafari, M.A. Economic and operational evaluation of PV and CHP combined with energy storage systems considering energy and regulation markets. In Proceedings of the 2020 IEEE Texas Power and Energy Conference (TPEC), College Station, TX, USA, 6–7 February 2020; pp. 1–6.
21. Harish, V.S.K.V.; Anwer, N.; Kumar, A. Applications, planning and socio-techno-economic analysis of distributed energy systems for rural electrification in India and other countries: A review. *Sustain. Energy Technol. Assess.* **2022**, *52*, 102032. [CrossRef]
22. Kou, G.; Yüksel, S.; Dinçer, H. Inventive problem-solving map of innovative carbon emission strategies for solar energy-based transportation investment projects. *Appl. Energy* **2022**, *311*, 118680. [CrossRef]
23. Dong, W.; Zhao, G.; Yüksel, S.; Dinçer, H.; Ubay, G.G. A novel hybrid decision making approach for the strategic selection of wind energy projects. *Renew. Energy* **2022**, *185*, 321–337. [CrossRef]
24. Zhao, Y.; Korsakienė, R.; Dinçer, H.; Yüksel, S. Identifying Significant Points of Energy Culture for Developing Sustainable Energy Investments. *SAGE Open* **2022**, *12*, 21582440221087262. [CrossRef]
25. McGovern, G. Capturing community value in civic energy business model design. *Energy Policy* **2021**, *156*, 112468. [CrossRef]
26. De Martini, P.; Gallagher, L.; Takayesu, E.; Hanley, R.; Henneaux, P. Unlocking Consumer DER Potential: Consumer-Centric Approaches for Grid Services. *IEEE Power Energy Mag.* **2022**, *20*, 76–84. [CrossRef]
27. Liu, W.; Ding, F. Hierarchical distribution system adaptive restoration with diverse distributed energy resources. *IEEE Trans. Sustain. Energy* **2020**, *12*, 1347–1359. [CrossRef]
28. Chen, J.; Zhou, Z.; Karunakaran, V.; Zhao, S. An efficient technique-based distributed energy management for hybrid MG system: A hybrid QOCSOS-RF technique. *Wind Energy* **2020**, *23*, 575–592. [CrossRef]
29. Carayannis, E.G.; Dezi, L.; Gregori, G.; Calo, E. Smart environments and techno-centric and human-centric innovations for Industry and Society 5.0: A quintuple helix innovation system view towards smart, sustainable, and inclusive solutions. *J. Knowl. Econ.* **2021**, *13*, 926–955. [CrossRef]
30. Carayannis, E.G.; Grigoroudis, E.; Wurth, B. OR for entrepreneurial ecosystems: A problem-oriented review and agenda. *Eur. J. Oper. Res.* **2021**, *300*, 791–808. [CrossRef]
31. Carayannis, E.G.; Christodoulou, K.; Christodoulou, P.; Chatzichristofis, S.A.; Zinonos, Z. Known unknowns in an era of technological and viral disruptions—Implications for theory, policy, and practice. *J. Knowl. Econ.* **2022**, *13*, 587–610. [CrossRef]
32. Kostis, P.; Dinçer, H.; Yüksel, S. Knowledge-Based Energy Investments of European Economies and Policy Recommendations for Sustainable Development. *J. Knowl. Econ.* **2022**. [CrossRef]
33. Dinçer, H.; Yüksel, S.; Martínez, L. Collaboration enhanced hybrid fuzzy decision-making approach to analyze the renewable energy investment projects. *Energy Rep.* **2022**, *8*, 377–389. [CrossRef]
34. Wang, Z.; Geng, Z.; Fang, X.; Tian, Q.; Lan, X.; Feng, J. The Optimal and Economic Planning of a Power System Based on the Microgrid Concept with a Modified Seagull Optimization Algorithm Integrating Renewable Resources. *Appl. Sci.* **2022**, *12*, 4743. [CrossRef]
35. Niu, J.; Tian, Z.; Zhu, J.; Yue, L. Implementation of a price-driven demand response in a distributed energy system with multi-energy flexibility measures. *Energy Convers. Manag.* **2020**, *208*, 112575. [CrossRef]
36. Xu, B.; Luo, Y.; Xu, R.; Chen, J. Exploring the driving forces of distributed energy resources in China: Using a semiparametric regression model. *Energy* **2021**, *236*, 121452. [CrossRef]
37. Wan, Q.; Zhao, X.; Liu, H.; Dinçer, H.; Yüksel, S. Assessing the New Product Development Process for the Industrial Decarbonization of Sustainable Economies. *SAGE Open* **2022**, *12*, 21582440211067231. [CrossRef]
38. Kou, G.; Deverick, J.; Phelps, K.; Nguyen, T.; Velez-Cedeno, F.G. Impact of distributed energy resources on arc flash incident energy. *IEEE Trans. Power Deliv.* **2019**, *35*, 531–539. [CrossRef]
39. Baodi, D.; Kai, C.; Meng, C.; Ying, Z.; Zhuandi, H.; Xiaoyun, Q. Design and Application of Regional Multi-energy Complementary Distributed Energy Management and Control Platform Based on Big Data. In Proceedings of the 2020 IEEE/IAS Industrial and Commercial Power System Asia (I&CPS Asia), Weihai, China, 13–15 July 2020; pp. 121–126.
40. Zalengera, C.; To, L.S.; Sieff, R.; Mohr, A.; Eales, A.; Cloke, J.; Batchelor, S. Decentralization: The key to accelerating access to distributed energy services in sub-Saharan Africa? *J. Environ. Stud. Sci.* **2020**, *10*, 270–289. [CrossRef]
41. Vasiliev, M.; Alameh, K. Recent developments in solar energy-harvesting technologies for building integration and distributed energy generation. *Energies* **2019**, *12*, 1080. [CrossRef]
42. Kaplan, R.S.; Norton, D.P.; Horváth, P. *Balanced Scorecard*; Schäffer-Poeschel: Stuttgart, Germany, 1997.
43. Kaplan, R.S.; Norton, D.P. Balanced Scorecard. In *Das Summa Summarum Des Management*; Gabler: Oslo, Norway, 2007; pp. 137–148.
44. Atanassov, K.T. Intuitionistic Fuzzy Sets. In *Intuitionistic Fuzzy Sets*; Physica: Heidelberg, Germany, 1999; pp. 1–137.
45. Yager, R.R. Pythagorean Fuzzy Subsets. In Proceedings of the 2013 Joint IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS), Edmonton, AB, Canada, 24–28 June 2013; IEEE: Piscataway, NJ, USA, 2013; pp. 57–61.
46. Yager, R.R. Generalized orthopair fuzzy sets. *IEEE Trans. Fuzzy Syst.* **2016**, *25*, 1222–1230. [CrossRef]
47. Zhang, W.R. Bipolar fuzzy sets and relations: A computational framework for cognitive modeling and multiagent decision analysis. In Proceedings of the First International Joint Conference of The North American Fuzzy Information Processing Society Biannual Conference, San Antonio, TX, USA, 18–21 December 1994; pp. 305–309.

48. Kafka, K.I.; Dinçer, H.; Yüksel, S. Impact-Relation Map of Innovative Service Development Regarding the Sustainable Growth for Emerging Markets. *J. Knowl. Econ.* **2022**. [CrossRef]
49. Belluscio, V.; Iosa, M.; Vannozzi, G.; Paravati, S.; Peppe, A. Auditory Cue Based on the Golden Ratio Can Improve Gait Patterns in People with Parkinson's Disease. *Sensors* **2021**, *21*, 911. [CrossRef]
50. Keršuliene, V.; Zavadskas, E.K.; Turskis, Z. Selection of rational dispute resolution method by applying new step-wise weight assessment ratio analysis (SWARA). *J. Bus. Econ. Manag.* **2010**, *11*, 243–258. [CrossRef]
51. Benayoun, R.; Roy, B.; Sussman, B. ELECTRE: Une méthode pour guider le choix en présence de points de vue multiples. *Note De Trav.* **1966**, *49*, 43.
52. Elahi, M.; Ricci, F.; Repsys, V. System-wide effectiveness of active learning in collaborative filtering. In Proceedings of the International Workshop on Social Web Mining, Co-located with IJCAI, Barcelona, Spain, 18 July 2011.
53. *World Energy Outlook 2022, October*; EIA: Washington, DC, USA, 2022.
54. Triodos. Powerful Potential—Financing Renewable Energy in Emerging Markets. Triodos Investment Managements. 2021. Available online: https://www.responsible-investor.com/powerful-potential-financing-renewable-energy-in-emerging-markets/ (accessed on 30 October 2022).
55. Yucesan, M.; Kahraman, G. Risk evaluation and prevention in hydropower plant operations: A model based on Pythagorean fuzzy AHP. *Energy Policy* **2019**, *126*, 343–351. [CrossRef]
56. Kulisic, B.; Dimitriou, I.; Mola-Yudego, B. From preferences to concerted policy on mandated share for renewable energy in transport. *Energy Policy* **2021**, *155*, 112355. [CrossRef]
57. Lv, Z.; Kong, W.; Zhang, X.; Jiang, D.; Lv, H.; Lu, X. Intelligent security planning for regional distributed energy internet. *IEEE Trans. Ind. Inform.* **2019**, *16*, 3540–3547. [CrossRef]
58. Shi, Q.; Li, F.; Olama, M.; Dong, J.; Xue, Y.; Starke, M.; Kuruganti, T. Network reconfiguration and distributed energy resource scheduling for improved distribution system resilience. *Int. J. Electr. Power Energy Syst.* **2021**, *124*, 106355. [CrossRef]
59. Gissey, G.C.; Zakeri, B.; Dodds, P.E.; Subkhankulova, D. Evaluating consumer investments in distributed energy technologies. *Energy Policy* **2021**, *149*, 112008. [CrossRef]
60. Kaplan, R.S.; Norton, D.P. Strategic learning & the balanced scorecard. *Strategy Leadersh.* **1996**, *24*, 18–24.
61. Carayannis, E.G.; Goletsis, Y.; Grigoroudis, E. Composite innovation metrics: MCDA and the Quadruple Innovation Helix framework. *Technol. Forecast. Soc. Chang.* **2018**, *131*, 4–17. [CrossRef]
62. Carayannis, E.G.; Grigoroudis, E.; Goletsis, Y. A multilevel and multistage efficiency evaluation of innovation systems: A multi-objective DEA approach. *Expert Syst. Appl.* **2016**, *62*, 63–80. [CrossRef]
63. Can, M.; Ahmed, Z.; Ahmad, M.; Oluc, I.; Guzel, I. The Role of Export Quality in Energy–Growth Nexus: Evidence from Newly Industrialized Countries. *J. Knowl. Econ.* **2022**, 1–19. [CrossRef]
64. Komninos, N.; Kakderi, C.; Mora, L.; Panori, A.; Sefertzi, E. Towards high impact smart cities: A universal architecture based on connected intelligence spaces. *J. Knowl. Econ.* **2022**, *13*, 1169–1197. [CrossRef]
65. Saadaoui, H.; Chtourou, N. Do Institutional Quality, Financial Development, and Economic Growth Improve Renewable Energy Transition? Some Evidence from Tunisia. *J. Knowl. Econ.* **2022**. [CrossRef]
66. Pacific, Y.K.T.; Magalie, N.M.A.G. One Bad Turn Deserves Another: How Energy Production, Financial Instability, and Political Governance Crisis Sustain the Decline of FDI Inflows in the Central African Republic. *J. Knowl. Econ.* **2022**. [CrossRef]
67. Li, X.; Lim, M.K.; Ni, D.; Zhong, B.; Xiao, Z.; Hao, H. Sustainability or continuous damage: A behavior study of prosumers' electricity consumption after installing household distributed energy resources. *J. Clean. Prod.* **2020**, *264*, 121471. [CrossRef]
68. Sarmiento-Vintimilla, J.C.; Torres, E.; Larruskain, D.M.; Pérez-Molina, M.J. Applications, Operational Architectures and Development of Virtual Power Plants as a Strategy to Facilitate the Integration of Distributed Energy Resources. *Energies* **2022**, *15*, 775. [CrossRef]
69. Fonseca, J.D.; Camargo, M.; Commenge, J.M.; Falk, L.; Gil, I.D. Trends in design of distributed energy systems using hydrogen as energy vector: A systematic literature review. *Int. J. Hydrogen Energy* **2019**, *44*, 9486–9504. [CrossRef]
70. Donnellan, P.R.; Kase, W. The Future of Energy: Cleaner, Distributed and Customer-Centric. *IEEE Eng. Manag. Rev.* **2019**, *47*, 21–23. [CrossRef]
71. Sun, L.; Peng, J.; Dinçer, H.; Yüksel, S. Coalition-oriented strategic selection of renewable energy system alternatives using q-ROF DEMATEL with golden cut. *Energy* **2022**, *256*, 124606. [CrossRef]
72. Li, W.; Yüksel, S.; Dinçer, H. Understanding the financial innovation priorities for renewable energy investors via QFD-based picture fuzzy and rough numbers. *Financ. Innov.* **2022**, *8*, 67. [CrossRef]
73. Dinçer, H.; Yüksel, S.; Aksoy, T.; Hacıoğlu, Ü. Application of M-SWARA and TOPSIS methods in the evaluation of investment alternatives of microgeneration energy technologies. *Sustainability* **2022**, *14*, 6271. [CrossRef]
74. Štilić, A.; Puška, A.; Đurić, A.; Božanić, D. Electric Vehicles Selection Based on Brčko District Taxi Service Demands, a Multi-Criteria Approach. *Urban Sci.* **2022**, *6*, 73. [CrossRef]
75. Aghazadeh, E.; Yildirim, H.; Kuruoglu, M. A Hybrid Fuzzy MCDM Methodology for Optimal Structural System Selection Compatible with Sustainable Materials in Mass-Housing Projects. *Sustainability* **2022**, *14*, 13559. [CrossRef]
76. Özdağoğlu, G.; Özdağoğlu, A.; Damar, M. Identifying and prioritising process portfolio for sustaining an effective business process management lifecycle. *J. Multi-Criteria Decis. Anal.* **2022**. [CrossRef]

77. Ying, C.; Slamu, W.; Ying, C. Multi-Attribute Decision Making with Einstein Aggregation Operators in Complex Q-Rung Orthopair Fuzzy Hypersoft Environments. *Entropy* **2022**, *24*, 1494. [CrossRef]
78. Liu, P.; Ali, Z.; Mahmood, T. Archimedean Aggregation Operators Based on Complex Pythagorean Fuzzy Sets Using Confidence Levels and Their Application in Decision Making. *Int. J. Fuzzy Syst.* **2022**. [CrossRef]
79. Kamacı, H.; Marinkovic, D.; Petchimuthu, S.; Riaz, M.; Ashraf, S. Novel Distance-Measures-Based Extended TOPSIS Method under Linguistic Linear Diophantine Fuzzy Information. *Symmetry* **2022**, *14*, 2140. [CrossRef]