

RESEARCH ARTICLE

Open Access

Application of Robust Mathematical Optimization Approach in Solving the Problem of Selecting Energy Supply Methods for Blockchain Technology in Industrial Environments

Akram Ali Kazemi¹, Akbar Alam Tabriz^{2*}, Ali Rezaian³

Abstract

The purpose of this research is to select the best energy supply methods for blockchain technology and to optimize the use of each of the selected methods. For this purpose, a two-part hybrid approach based on best-worst multi-criteria decision making methods, VIKOR method and mathematical programming model has been used under uncertainty conditions. To implement this approach, first by reviewing the literature, the effective criteria in selecting the best method were extracted and then, the options or energy supply methods using blockchain technology were determined based on the experts' opinion. Finally, the weight of the criteria and the final ranking of the selected options were determined by the best-worst and VIKOR methods, respectively. In the second part, in order to determine the optimal amount of using available facilities for blockchain technology to implement the selected method, a robust mathematical model is designed in which the NPV criterion is used as an economic evaluation measure of using the selected method in the first part. As the obtained results show, the criteria of "implementability" and "productivity level" and "coordination with consumption pattern correction policies" have the highest level of importance with the weight of 0.339, 0.14 and 0.14, respectively, in order to choose the best option. Also, the best score compared to other options belongs to the energy supply method "electricity generation from the combined use of national grid and solar panels". Solving the mathematical model shows that the highest level of economic efficiency belongs to the use of solar panels to provide a significant part of the need for power.

Keywords: *Energy Supply Methods, Economic Evaluation, Best-Worst Method, VIKOR method, Robust Planning*

Introduction

Energy has played a role in societies as one of the most important factors of development and progress in recent decades. In this regard, facing challenges like the limitation of natural resources, environmental pollution and increasing energy needs due to technological progress, rapid increase in global population and climate change has become an important matter. Therefore, in order to provide solutions to improve efficiency, reduce costs and preserve the environment, a lot of research has been done

in the field of energy supply. In the meantime, blockchain is one of the technologies that has recently attracted a lot of attention [1]. This technology was first introduced in the form of technology supporting digital currencies or cryptocurrencies such as Bitcoin. Nevertheless, as one of the most useful tools, this technology is now used in various industries. As a distributed and intermediary-free platform, blockchain is widely used to record and verify transactions. Also, this technology is able to create a safe and reliable infrastructure for energy supply because it

1. Phd student of industrial management, Qazvin Branch, Islamic Azad University, Qazvin, Iran

2*. Professor, Department of Management, Shahid Beheshti University, Tehran, Iran (Corresponding author: a-tabriz@sbu.ac.ir)

3. Professor, Department of Management, Shahid Beheshti University, Tehran, Iran

has features such as security, transparency and immutability in data [2].

In the energy industry, the use of blockchain can have a significant impact on the energy supply process. Reducing costs, increasing the speed of transactions and creating a secure environment for information transfer are among the benefits of using blockchain. Of course, more studies are needed in the field of energy supply using this technology so that its potential can be fully utilized to significantly improve the energy supply process [3]. In general, it can be said that blockchain, as an innovative and reliable technology, can play an important role in improving energy supply processes and reducing the negative effects on the environment, considering the challenges facing global communities in the field of energy and development. In order to optimally use this technology and provide appropriate solutions to face energy challenges, there is still a need for numerous researches and cooperation between different industries.

As a new opportunity to improve processes and increase efficiency, blockchain can be used in the field of energy supply. Reducing costs, increasing the speed of transactions, and creating a secure environment for information transfer are the features with which blockchain is expected to help improve efficiency and reduce costs in energy supply. So far, the topic of using blockchain to improve energy supply processes, creating smart energy grids, and solving existing problems in this field has been investigated in many researches [4]. Features such as high security, fast transactions and doing transactions in a transparent manner are capabilities of blockchain that can significantly improve energy supply processes. Due to the possibility of storing data immutably and securely in the blockchain, it can be used to improve efficiency and reduce costs associated with these processes through accurate recording of all stages of production, transmission, and energy consumption. Also, the use of blockchain improves the processes

of transferring information and financial transactions in the field of energy supply and making these processes faster, which helps to increase productivity and reduce related costs [5].

In addition, the issue of creating smart energy grids using blockchain has been realized for some time. In this way, blockchain can help create a smart grid with the ability to connect smart devices and measure the data sent by them, and thus, help improve efficiency and better manage energy resources. Such a grid can help to optimize energy consumption, reduce energy waste, and thus save energy costs, which is possible through recording data related to energy consumption and consumption patterns. Therefore, the important issue here is the optimal choice of energy supply methods using blockchain. As a result, the optimal choice of energy supply methods is considered as a complex challenge due to the need to consider various variables such as cost, efficiency, and environmental effects. In this regard, multi-criteria decision-making methods and mathematical models can be used to solve this challenge. By optimizing the selection of energy supply methods, these approaches lead to improved efficiency and reduced costs related to energy supply [6].

In order to optimize the selection of energy supply methods for blockchain technology in industrial environments, the current research introduces a two-part hybrid approach using multi-criteria decision making and mathematical programming model. By combining various criteria, including efficiency, cost, sustainability and environmental impact, this approach ensures the selection of the best energy supply methods. To implement such an approach, first by reviewing the relevant literature, the effective criteria in selecting the best methods are extracted and then, these methods are ranked by multi-criteria decision-making approaches. Of course, selecting the best methods is not the only purpose of this research, but it is also aimed to optimize the way of using these methods. The mathematical models proposed in this

section provide the possibility of optimizing the use of the available facilities to implement the selected method. By using economic indicators such as Net Present Value (NPV), as one of the main criteria of economic evaluation, these models ensure the selection of the best solutions. The problem of optimal selection of energy supply methods for blockchain technology has been systematically investigated at this research stage. The investigation carried out in this research not only improves efficiency in energy supply by providing analytical methods and mathematical models, but also provides the necessary information to select the best possible solutions for managers and decision makers in this field. Improving efficiency, reducing costs and preserving the environment in the energy industry are among the most important effects of using these optimization approaches, which creates a reliable and optimal process for selecting the best energy supply methods using blockchain technology.

Literature Review

Efforts to develop alternative models that place a higher priority on reducing environmental impacts have been made in response to concerns about the environmental impacts of traditional cryptocurrencies. Among other things, alternative cryptocurrencies, often referred to as "green cryptocurrencies", have been developed with the aim of reducing the environmental impacts associated with the mining and validation processes of digital currencies [7]. Using such methods will optimize performance, reduce energy consumption, and manage environmental concerns. As such, the future blockchain industry is significantly influenced by sustainability considerations. Therefore, the aim of ongoing research and innovation in this industry is to create more robust and efficient cryptographic solutions that help the growth and adoption of blockchain-based digital currencies and at the same time, align with environmental goals [8].

On the other hand, a lot of media attention has recently been focused on the increasing energy consumption of cryptocurrencies, especially after the announcement by Elon Musk, the CEO of Tesla in May 2021 that due to the environmental problems related to the energy consumption of the Bitcoin digital currency, Tesla will stop accepting payments in this currency. This decision fueled discussions about the sustainability of cryptocurrencies by raising awareness about the issue [9]. Also, the increase in energy consumption of cryptocurrencies has been confirmed in research conducted by institutions such as the Broker School at the University of Cambridge. Based on these studies, empirical evidence and data have been obtained that are a factor in attracting support for the problems raised about the environmental impact of cryptocurrencies and increasing the continuous dialogue about their sustainability [8].

Due to the secrecy of many computing facilities or mines and the lack of records of their electricity consumption, it is not possible to directly track the total power consumption in today's cryptocurrency grids. Of course, analytical measurements of electricity consumption are possible [10]. Since this facility continuously consumes electricity, cryptocurrency mining operations increase the load factor and put pressure on the power system during peak hours. In this way, we face a reduction in the useful life of the equipment, a power cut for other customers, and an increase in the risk of fire [11]. Increased demand for electricity due to cryptocurrency mining activities can lead to higher electricity rates for local customers. Local consumers may still pay costs such as the cost of upgrading raw infrastructure needed to support mining operations in the region even if mining activities are moved to other locations due to conditions or regulations [12]. For the cryptocurrency sector and the planet in general, the path to a more sustainable and environmentally friendly future requires understanding and supporting green blockchain projects. For the following reasons, awareness of green

blockchain-based efforts and activities is critical [13].

- Especially those based on the PoW algorithm, traditional blockchain grids have been criticized for consuming too much energy and emitting too much carbon dioxide.
- Since the awareness of environmental issues is becoming more and more important for customers and companies, the use of green blockchain solutions can show commitment to corporate social responsibility and sustainability.
- More stringent environmental regulations may be imposed on blockchain grids by governments and regulatory agencies. Businesses and individuals can keep pace with regulatory changes by being aware of and supporting green blockchain activities.
- Green blockchain solutions and research on sustainable energy consensus algorithms are being developed through green blockchain efforts. Hence, the blockchain industry may experience greater adoption and improved productivity from these developments.
- Supporting such activities can help increase the company's reputation and attract environmentally aware customers, investors and partners.

Green BC technology can be used in various fields [14]. Since it is compatible

with an environmentally friendly approach, green blockchain can be used in industries where sustainability and reducing carbon footprints are critical [15]. Among other things, it can be used in the field of renewable energy, agriculture and forestry, all of which require the follow-up and verification of environmentally acceptable operations [16]. Also, due to the efficient design of energy, green blockchain can be very useful in the energy industry, for instance by facilitating sustainable energy projects, effective management of grids and improving energy distribution [16]. Green blockchain also improves experience and transparency and is therefore a good option for supply chain management [17]. This issue is important, especially in important sectors such as food and pharmaceutical products, where the verification of the credibility and quality of products is essential. In the financial industry, green blockchain can simplify transactions, eliminate middlemen, and use the least amount of energy, which saves money and sustains the environment [18]. Mitigating climate change by facilitating carbon credit trading, tracking emissions, and incentivizing environmentally friendly practices is another area that could benefit from green blockchain [19]. Finally, green blockchain can enable efficient and secure data exchange in a variety of systems, from energy management to transportation [16]. The most important research related to energy source selection is presented in Table 1.

Table 1.

Literature review of energy selection methods

Authors	Criteria	Method	Best resource	Field	Country
[20]	Economic, technical, social, environmental	SMAA	Biomass	Domestic	Finland
[21]	Economic, technical, social, environmental, political	AHP-ARAS	Hydraulic	Domestic	Lithuania
[22]	Economic, technical, social, environmental, political	AHP	solar	Domestic	Saudi Arabia
[23]	Economic, technical, social	ANP-VIKOR	solar	Industry	Turkey
[24]	economic, technical, social, environmental,	SMAA	solar	Tourism	Finland
[25]	Economic, technical, social, environmental, political	PROMETHEE	solar	Domestic	Spain

Authors	Criteria	Method	Best resource	Field	Country
[26]	Economic, technical, social, environmental	TOPSIS	solar	Domestic	Bangladesh
[27]	Economic, technical, social, environmental	PROMETHEE	Wind	Tourism	Greece
[28]	Economic, technical, social	GIS-AHP	solar	Domestic	Netherlands
[29]	Economic, technical, social, environmental, political	AHP	solar	Domestic	Algeria
[30]	Political, economic, technical, environmental	VIKOR	Wind	Industry	India
[31]	Economic, technical, environmental, political	ANP-PROMETHEE	Hydraulic	Domestic	china
[32]	Technical, environmental	GIS	solar	Domestic	Egypt
[33]	Political, economic, technical, environmental	ARAS	Biomass	Agriculture	India
[34]	Economic, technical, social and environmental	TOPSIS	Wind	Domestic	India
[35]	Economic, technical, social and environmental	ANP-VIKOR	Wind	Domestic	china

Research problem statement

The purpose of this research is to examine the problem of selecting energy supply methods for blockchain technology, in this regard, first by studying the literature, the effective criteria for selecting the best method were extracted and then, several required energy supply methods were proposed as the options based on the experts opinion. In the next step, the weights of the criteria are determined using the best-worst method and the final ranking of the selected options is done using the VIKOR method. In the second part, in order to determine the optimal amount of use of the available facilities for the implementation of the selected method, a robust mathematical model is designed, in which, the NPV is used as a measure of the economic evaluation of the using the method selected in the first part.

The research problem is designed based on the latest studies conducted in the field of energy consumption optimization and consumption pattern modification. According to this research, one of the ongoing projects is the use of solar panels in the free spaces of industrial environments in order to meet the need for electric energy, which is directly stored and used by the panels in the batteries. In this research, the important problem under discussion is how much of the available free area should be

used for loading solar panels in each industrial area. The optimal situation for the decision-maker occurs when the initial costs of building a local power plant and the costs of using the existing grid, as well as the income from the sale of electricity to the distribution grid, reach the optimal level. In other words, every company active in the field of blockchain technology infrastructure development should determine how much of its space to allocate to the panels, so that the initial cost will be returned in a certain period of time and reduce supply costs of blockchain energy in the long run.

Designing the energy supply system to use blockchain technology will be a very difficult task due to the existence of many complexities in making appropriate decisions. These problems are presented as issues that this research aims to answer. The most important of these issues is determining the period of use of each of the energies. Each type of energy supply method has its own initial costs, therefore, these costs should be justified in the long run. Since energy supply systems can have different conditions of use, according to the costs, it should be decided whether the necessary conditions for the development of the infrastructure using blockchain technology are available or not? Also, in each period, attention should be paid to the level of available budget and the level

of demand of each type of energy in order to cover the operation. For this purpose, the multi-criteria decision-making methods used and the mathematical model of the research are explained.

Multi-criteria decision making methods

The definitions of best-worst method and VIKOR technique are briefly presented below.

Describing the best-worst method

As one of the powerful methods in solving MCDM problems, this method is used to obtain the weights of options and criteria [36, 37] and can overcome the weaknesses of methods based on pairwise comparisons (e.g. AHP and ANP) such as inconsistency. It also significantly reduces the number of pairwise comparisons by only performing reference comparisons. BWM has been used in recent years by many researchers to determine weights and rank options in different fields. The general structure of the BWM method includes the following steps:

Step 1. Creating the decision criterion system: The decision criterion system includes the set of criteria identified through the literature review and experts' opinions, and they are considered as $\{c_1, c_2, \dots, c_n\}$. The values of decision criteria can reflect the performance of different options.

Step 2. Determining the best and worst among the main criteria as well as sub-criteria: based on the decision criteria system, the best and worst criteria should be identified by decision makers. The best and worst criteria are denoted by the symbols c_B and w_B , respectively.

Step 3. Making reference comparisons for the best criterion: the priority of the best criterion compared to other criteria is determined in this step by using numbers between 1 and 9 based on the verbal scale presented in table (5). The results of this vector are shown as follows:

$$A_B = (a_{B1}, a_{B2}, \dots, a_{Bn}) \quad (1)$$

So that a_{Bj} shows the priority of the best selected criterion B with respect to each criterion j. Clearly, $a_{BB} = 1$.

Step 4. Performing reference comparisons for the worst criterion: Similarly, the priority of all criteria is calculated relative to the selected worst criterion using numbers between 1 and 9. The results of this vector are shown as follows:

$$A_w = (a_{1W}, a_{2W}, \dots, a_{nW})^T \quad (2)$$

So that a_{jW} shows the priority of each criterion j compared to the worst selected criterion of W. Clearly, $a_{WW} = 1$.

Step 5. Determining the optimal weights ($W_1^*, W_2^*, \dots, W_n^*$): In this step, the maximum absolute difference $\{|w_B - a_{Bj}w_j|, |w_j - a_{jW}w_W|\}$ is minimized for all j in order to achieve the optimal weights of the criteria which is formulated as the following optimization problem:

$$\begin{aligned} \min \max_j \{ & |w_B - a_{Bj}w_j|, \\ & |w_j - a_{jW}w_W| \} \\ \text{S. t.} & \\ & \sum_j w_j = 1 \\ & w_j \\ & \geq 0, \text{ for all } j \end{aligned} \quad (3)$$

Problem (3) can be transformed into the following model:

$$\begin{aligned} \min \xi^L & \\ \text{S. t.} & \\ & |w_B - a_{Bj}w_j| \\ & \leq \xi^L, \text{ for all } j \\ & |w_j - a_{jW}w_W| \\ & \leq \xi^L, \text{ for all } j \\ & \sum_j w_j = 1 \\ & w_j \\ & \geq 0, \text{ for all } j \end{aligned} \quad (4)$$

Since the Model (4) is linear and has a unique solution, the optimal weights ($w_1^*, w_2^*, \dots, w_n^*$) and the optimal value ξ^{L*} are obtained by solving this model. For the above model, values close to zero ξ^{L*} indicate a high level of compatibility [37].

VIKOR method

The VIKOR technique is a compromise ranking method and is often used when there

are different conflicting criteria [38]. This method creates a compromise solution based on "closeness to the ideal solution and mutual agreement through concessions". This method has been widely used by many researchers to rank options. The steps of VIKOR method are presented below [39]:

Step 1: Obtaining a pair matrix for each option so that each criterion is evaluated using the verbal scale presented in Table (4).
Step 2: Calculating the average decision matrix using equation (5).

$$f_{ij} = \frac{1}{k} \sum_{t=1}^k x_{ij}^t \quad i = 1, 2, \dots, m; j = 1, 2, \dots, n \quad (5)$$

So that x_{ij}^t is the value of the i th option compared to the j th criterion by the t th expert.
Step 3: Calculating the best f_j^* and the worst f_j^- values for all criteria using equations (6) and (7).

$$f_j^* = \max f_{ij}, \quad (6)$$

$$i = 1, 2, \dots, m; j = 1, 2, \dots, n$$

$$f_j^- = \min f_{ij}, \quad (7)$$

$$i = 1, 2, \dots, m; j = 1, 2, \dots, n$$

where f_j^* and f_j^- show the positive ideal solution and negative ideal solution for the j th criterion, respectively.

Step 4: Calculating the S_i and R_i values for $i=1,2,\dots,m$ using equations (8) and (9).

$$S_i = \sum_{j=1}^n w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)} \quad (8)$$

$$R_i = \max \left[w_j \frac{(f_j^* - f_{ij})}{(f_j^* - f_j^-)} \right] \quad (9)$$

where S_i shows the distance of the i th option from the positive ideal solution, R_i indicates the distance of the i th option from the negative ideal solution, and w_j shows the weights of the factors obtained through fuzzy BWM analysis.

Step 5: Calculating the Q_i value based on equation (10).

$$Q_i = v \left[\frac{S_i - S^*}{S^- - S^*} \right] + (1 - v) \left[\frac{R_i - R^*}{R^- - R^*} \right] \quad (10)$$

where $S^- = \max_i S_i$, $S^* = \min_i S_i$ and $R^- = \max_i R_i$, $R^* = \min_i R_i$ and the v parameter is introduced as a weight for the group maximum utility strategy, which is considered equal to 0.5 in this research.

Step 6: Ranking the options using Q_i values
Step 7: The options are ranked based on the minimum values obtained Q_i so that the following two conditions are true simultaneously:

The first condition (acceptance property): option A^1 is selected if $Q(A^2) - Q(A^1) \geq 1/m - 1$, so that A^2 is the option ranked second and m is equal to is the total number of options.

The second condition (consistency of acceptance in decision making): based on the values of S_i and/or R_i , A^1 must also obtain the first rank.

Step 8: The option with the lowest value in Q_i is ranked first.

Robust mathematical optimization model

Robust optimization obtains a set of responses that are robust against fluctuations of parameters (input data) in the future. A robust optimization approach is presented by Mulvey, which is able to take the decision maker's inconsistency risk or service level function and provide a set of responses that is less sensitive to the realization of the data in the set of scenarios. Two types of robustness are introduced in this approach: response robustness (response close to optimal in all scenarios) and model robustness (response close to feasibility in all scenarios). The optimal response obtained by the robust optimization model is called robust. If the input data changes then it remains close to the optimum, it is called response robustness. A response is called robust if it is approximately justified for small changes in the input data. This is called robustness model. Robust

optimization includes two specific limitations: 1) structural constraint 2) control constraint. Structural constraint is a concept of linear programming and the input data are deterministic and fixed and away from any disturbances, while control constraints are formulated as auxiliary constraints that are affected by non-deterministic data. The robust optimization framework is briefly explained below. First, $x \in R^{n_1}$ is the vector of design variables and $y \in R^{n_2}$ is the vector of control variables. The robust optimization model is as follows:

$$\text{Min } c^T x + d^T y \quad (11)$$

$$Ax = b \quad (12)$$

$$Bx + Cy = e \quad (13)$$

$$x, y \geq 0 \quad (14)$$

Constraint (12) is a structural constraint with the fixed and definite coefficients. Constraint (13) is a control constraint with uncertain coefficients influenced by the scenario. Constraint (14) also ensures the non-negativity of the variables. The formulation of the robust optimization problem includes a set of scenarios $\tau = \{1, 2, \dots, S\}$. Under each scenario $S \in \tau$, the coefficients of the control constraints with constant probability P_s are equal to $\{d_s, B_s, C_s, e_s\}$, where P_s represents the probability that each scenario occurs and $\sum_s P_s = 1$ is the optimal response of this robust model, if for any given scenario $S \in \tau$ remains close to optimal. This is called the robust model. There are situations where the answers we get for the above model may not be both feasible and optimal for all $S \in \tau$ scenarios. Here, the relationship between response robustness and model robustness is determined using multi-criteria decision-making concepts. Robust optimization model is formulated to measure this relationship. First of all, the control variable Y_s for each scenario $S \in \tau$ and the error vector δ_s , are introduced which measures the allowable non-feasibility in the control constraints under scenario s . Due to the non-deterministic parameters of the model, it may not be justified for some scenarios. Therefore, δ_s shows the non-feasibility of the model under scenario s . If the model is

feasible, δ_s will be equal to zero. Otherwise, δ_s will take a positive value according to the constraint (17). The optimization model is formulated based on the mathematical programming problem (15) to (18) as follows:

$$\text{Min } \sigma(x, y_1, \dots, y_s) + \omega \rho(\delta_1, \delta_2, \dots, \delta_s) \quad (15)$$

$$AX = b \quad (16)$$

$$B_s x + C_s y_s + \delta_s = e_s \quad (17)$$

$$x \geq 0, y \geq 0 \quad (18)$$

It should be noted that the first term of the objective function of choosing a unit for the objectives in the previous objective function (5), $\zeta_s = c^T x + d^T y$ is a random variable with a random value $\zeta_s = c^T x + d_s^T y_s$ and with probability P_s under scenario $S \in \tau$ because the robust optimization model considers multiple scenarios. In the formulation of random linear programming, the average value $\sigma(0) = \sum_s \zeta_s P_s$ is used and in fact the first term shows the response robustness. The second term in the objective function $\rho(\delta_1, \delta_2, \dots, \delta_s)$ is the justified penalty function, which penalizes the violation of the control constraints under some scenarios. Violation of the control constraints means that under some problem scenarios, an unjustified answer is obtained. By using the weight ω , the relationship between the robustness of the response, which is measured from the first term $\sigma(0)$, and the model robustness, which is measured from the penalty function $\rho(0)$, can be modeled under multi-criteria decision making. For instance, if $\omega(0)$ is the objective of minimizing the term $\sigma(0)$ and the possible answer is unjustified. While if ω becomes large enough, the term $\rho(0)$ dominates and leads to more cost. Studying on choosing the appropriate form of $\rho(0)$ and $\sigma(0)$ can be seen in many studies. The expression $\sigma(x, y_1, \dots, y_s)$ is presented by Mulvey as follows:

$$\sigma(0) = \sum_s \zeta_s p_s + \lambda \left(\sum_s \zeta_s p_s - \sum_{s'} \zeta_{s'} p_{s'} \right)^2 \quad (19)$$

The variance of equation (19) to show the response robustness, indicates that the decision has a high risk. In other words, a small variable in parameters with uncertainty can cause large changes in the value of the measurement function. λ is the weight assigned to the response variance. As can be seen, there is a quadratic expression in equation (19). To reduce computer operations, an absolute value expression has been used as follows instead of a quadratic expression:

$$\sigma(0) = \sum_s \gamma_s p_s + \lambda \sum_s p_s \left| \gamma_s - \sum_{s'} \gamma_{s'} p_{s'} \right| \quad (20)$$

Symbols and sets

t set of potential technologies available for energy generation
 i set of potential energies available (national grid and solar panels)
 s set of scenarios

Parameters

D_{is} Value of each energy type i under scenario s
 Cap Maximum allowed space (in terms of square footage) to use the solar energy generation system

Me_{its} Amount of energy i generated using technology t per one square meter of space under scenario s

N_i Number of technologies that can be used simultaneously to meet the energy needs of i

$Cost_{its}$ Cost of building energy generation site i with technology t under scenario s

$Price_{its}$ Cost of using energy i with technology t under scenario s

$Sale_{its}$ Sale price of energy i with technology t under scenario s

$Co2_{its}$ CO2 greenhouse gas production cost per use of energy i generated with technology t under scenario s

f interest rate

n waiting time for investment return

P_{its} Initial cost for building technology t in using energy i under scenario s

S size of the sector in each cost range for the desired energies

P_s Probability of the scenario

M arbitrary and large enough number

Decision variables

X_{its} Amount of generated energy i with technology t under scenario s

Y_{its} 1 if technology t is used to generate energy i under scenario s and zero, otherwise.

W_{its} Price increase factor of providing energy under scenario s

$$TC_s = \sum_{i \in I} \sum_{t \in T} Cost_{its} Y_{its} + \sum_{i \in I} \sum_{t \in T} W_{its} Price_{its} X_{its} + \sum_{i \in I} \sum_{t \in T} Co2_{its} X_{its} - \sum_{i \in I} \sum_{t \in T} Sale_{its} X_{its} \quad (21)$$

$$Min Z = \sum_s P_s TC_s + \lambda_1 \sum_s P_s \left| TC_s - \sum_{s'} P_{s'} TC_{s'} \right| + \omega \sum_s \sum_i \sum_t P_s \delta_{its} \quad (22)$$

s.t.

$$\sum_{t \in T} X_{its} + \delta_{its} \geq D_{is} \quad \forall i \in I, s \in S \quad (23)$$

$$X_{its} \leq M Y_{its} \quad \forall i \in I, t \in T, s \in S \quad (24)$$

$$Y_{its} \leq X_{its} \quad \forall i \in I, t \in T, s \in S \quad (25)$$

$$X_{its}/Me_{its} \leq Cap \quad \forall i \in I, t \in T, s \in S \quad (26)$$

$$\sum_{t \in T} Y_{its} \leq N_{is} \quad \forall t \in I, s \in S \quad (27)$$

$$X_{its}/S \leq W_{its} \quad (28)$$

$$W_{its} \in Integer, X_{its} \geq 0, Y_{its} \in \{0,1\} \quad \forall i \in I, t \in T, s \in S \quad (29)$$

The objective function is to minimize the net costs. The first sentence calculates the initial construction cost of each energy

generation site with each technology. The second sentence deals with the minimization of the cost of using each energy in each

technology. In this sentence, the coefficient W_{it} is used. This coefficient increases the price of providing energy in intervals of size (S). In fact, if the amount of energy produced is in the $[0, S]$ interval, the value of W_{it} is equal to 1 and only the main cost is calculated. Now, if the amount of generated energy is in the $[S, 2S]$ range, then the value of W_{it} is equal to 2 and the main cost is also 2 times. In this way, a function can be considered to increase the cost of using energy exponentially. The third sentence deals with the minimization of costs caused by CO₂ production. However, the fourth term of the objective function also deals with the calculation of profit from the sale of surplus energy generated in each technology. This sentence is important because it is possible to send the excess produced amount to the city power grid and receive its income in the production of electricity. Constraint (23) ensures that the demand is met using different technologies for each energy. Constraints (24) and (25) ensure that if a technology is used to generate energy, then some generation must take place and vice versa. Constraint (26) ensures that the amount of energy produced by any technology does not exceed the amount of allowed space (in terms of square footage). Constraint (27) specifies the number of technologies that can be used simultaneously to meet energy needs. Constraint (28) deals with the calculation of the cost level increase factor. Constraint (29) specifies the range of research variables.

However, due to the fact that a large initial cost must be incurred for the construction of some technologies, the initial cost must be changed to a periodic cost in order to make a correct comparison during the period. Therefore, in this research, through the use of the following formula, it is used to convert the initial cost into periodic cost.

$$\begin{aligned} & Cost_{it} \\ & = P_{it} \left[\frac{f(1+f)^n}{(1+f)^n - 1} \right] \quad \begin{matrix} \forall i \in I, t \\ \in T \end{matrix} \quad (30) \end{aligned}$$

Computational results analysis

Data analysis is a multi-stage process to summarize, code, categorize and process the data obtained through the use of collection tools in the statistical sample (community) to create various types of analysis and relationships between these data to achieve the research objectives. Regarding the process, data is refined both conceptually and empirically. In this section, it is tried to apply the approach and method described in the problem statement section, to analyze the data information align with of the research objective and to answer the research questions in a step-by-step manner.

The results of solving the best-worst method

The selection process is structured along the five steps of the best-worst method introduced in the problem statement section. This section will be implemented to complete the second stage (use of VIKOR method).

Determining the set of criteria

The set of criteria is determined based on the input information obtained from interviews with experts and decision makers of the studied company named Mehr Birjand housing. The information was collected during a number of interviews (eight interviewees, each lasting about an hour). During this interview, the respondents were asked to express their priorities regarding the most important effective criteria in determining the technology options considered in the field of energy. The criteria from the literature research were presented to the respondents as a starting point. Also, they were able to add their own criteria to the criteria obtained from the literature review. The list of final criteria is provided in the table below.

Table 2.

Criteria used in the selection final phase

Criterion	Sign
Implementability	C_1
Investment risk	C_2
Investment cost	C_3
Amount of economic savings	C_4
Productivity level	C_5
Cost of maintenance and repairs	C_6
Amount of environmental pollutants generation	C_7
Return of capital	C_8
Coordination with the consumption pattern correction plan	C_9

Determining the best and the worst criteria

The second step in the formation of the best-worst method is to determine the best and the worst criteria. The best criterion is the criterion identified by the respondents as the most important criterion in selecting electric energy generation technology, while the worst criterion is the one that is the least important in selecting electric energy

generation technology, according to the decision makers' opinion. This information was prepared through a short questionnaire. The results of the questionnaire indicate that according to experts, the criterion of "implementability" was selected as the best criterion and "maintenance and repair costs" was chosen as the worst criterion.

Determining the priority of the best criterion over other criteria

The third step includes identifying the preferences of the best criterion over other criteria. This information was also obtained using a questionnaire. Respondents are asked to compare the best selected criteria with each of the other criteria and evaluate their priority using values between 1 and 9. A score of 1 means that the importance is equal to the other criterion, and a score of 9 indicates that the most important criterion is much more preferred than the other criterion. The table below shows these results expressed in the comparison vectors of the best criterion with other criteria.

Table 3.

Comparison vectors of the best criterion against others

Interviewee code	Implementability	Investment risk	Investment cost	Economic savings rate	Productivity rate	Repair and maintenance cost	Production rate of environmental pollutants	Return on investment period	Coordination with the consumption pattern correction plan
1	1	5	6	7	3	9	7	6	3
2	1	4	5	6	2	9	6	5	2
3	1	5	6	7	3	9	7	6	3
4	1	6	7	8	4	9	8	7	4
5	1	3	4	5	2	9	5	4	2
6	1	6	5	8	2	9	8	5	4
7	1	4	7	6	4	9	6	7	2
8	1	5	4	7	3	9	5	6	3
Average	1	4.75	5.5	6.75	2.875	9	6.5	5.75	2.875

Determining the priority of other criteria over the worst criterion

The fourth stage of the best-worst method is similar to the third stage, except that the respondents are asked to consider their

preferences from other criteria based on the worst criteria. Again, a value between 1 and 9 is used. This result can be seen on the vectors in the table below.

Table 4.
Comparison vectors of other criteria relative to the worst criterion

Interviewee code	Implementability	Investment risk	Investment cost	Economic savings rate	Productivity rate	Repair an maintenance cost	Production rate of environmental pollutants	Return on investment period	Coordination with the consumption pattern correction plan
1	9	4	2	3	5	1	3	4	7
2	9	5	3	4	8	1	4	5	6
3	9	5	3	3	5	1	3	2	7
4	9	4	2	2	5	1	2	3	5
5	9	6	4	5	8	1	6	5	6
6	9	4	5	3	6	1	2	5	6
7	9	6	3	2	4	1	4	2	8
8	9	5	6	3	4	1	4	2	7
average	9	4.875	3.5	3.125	5.625	1	3.5	3.5	6.5

Determining the weights

The weights are defined by the linear model of the best-worst method for the answer obtained from the simple average. A simple weighted average for each criterion was calculated after filling the questionnaire by eight respondents, which can be seen in the last row of the above table. The linear model is as follows.

$$\begin{aligned}
 &\min \xi^L \\
 &\text{S. t.} \\
 &|w_1 - w_1| \leq \xi^L \\
 &|w_1 - 4.75w_2| \leq \xi^L \\
 &|w_1 - 5.5w_3| \leq \xi^L \\
 &|w_1 - 6.75w_4| \leq \xi^L \\
 &|w_1 - 2.875w_5| \leq \xi^L \\
 &|w_1 - 9w_6| \leq \xi^L
 \end{aligned}$$

$$\begin{aligned}
 &|w_1 - 6.5w_7| \leq \xi^L \\
 &|w_1 - 5.75w_8| \leq \xi^L \\
 &|w_1 - 2.875w_9| \leq \xi^L \\
 &|w_1 - 9w_6| \leq \xi^L \\
 &|w_2 - 4.875w_6| \leq \xi^L \\
 &|w_3 - 3.5w_6| \leq \xi^L \\
 &|w_4 - 3.125w_6| \leq \xi^L \\
 &|w_5 - 5.625w_6| \leq \xi^L \\
 &|w_6 - w_6| \leq \xi^L \\
 &|w_7 - 3.5w_6| \leq \xi^L \\
 &|w_8 - 3.5w_6| \leq \xi^L \\
 &|w_9 - 6.5w_6| \leq \xi^L \\
 &\sum_j w_j = 1 \\
 &w_j \geq 0, \text{ for all } j
 \end{aligned}$$

The table below shows the results of solving the linear model.

Table 5.
Final weight of criteria

Criterion	Weight
Implementability	0.339
Investment risk	0.085
Investment cost	0.073
The amount of economic savings	0.060
Productivity level	0.140
Repairs & maintenance cost	0.031
amount of environmental pollutants generation	0.062
Return of capital	0.070
Coordination with the consumption pattern correction plan	0.140
ξ^L	0.064

ξ^L is the consistency index for comparisons. According to the table, the comparisons show a very high consistency as the value of ξ^L is close to zero. The five steps of the best-worst method are completed by determining the weights of the criteria.

VIKOR method

After calculating the weight of the criteria using the best-worst method and applying the

case study experts' opinion in this section, the options considered are prioritized using the VIKOR method during these steps:

Determining the options

The options raised in the problem were determined after reviewing the experts' opinions in the case study area, and the results are presented in the following Table 6:

Sign	Option (technology)
t_1	Solar power generation through joint venture
t_2	Electricity production from solar panels
t_3	Electricity generation through gas generator
t_4	Electricity generation from storage batteries
t_5	Electricity generation from wind turbines
t_6	Electricity generation from the combination of national grid and solar panels
t_7	Using the national grid

Normalized matrix

In this study, there are seven options and nine criteria. At first, the option-criteria matrix should be evaluated by experts. Then these values should be normalized according

to the equations mentioned in the previous section to be used in VIKOR method. The table below presents the option-criterion matrix and the normalized matrix.

Option-criterion matrix

Option	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
t_1	5.0	4.0	4.9	7.0	4.8	7.5	8.2	6.4	4.3
t_2	6.2	6.5	6.1	5.7	5.4	7.3	7.5	5.7	7.1
t_3	4.0	7.2	8.4	6.9	5.6	6.9	4.2	6.0	5.5
t_4	4.6	7.1	4.5	5.0	7.4	3.8	4.6	6.1	7.4
t_5	3.6	7.0	8.5	5.4	3.2	8.3	7.0	5.5	4.2
t_6	8.4	5.3	4.1	4.8	6.3	3.9	5.4	7.5	4.3
t_7	6.8	8.5	3.8	4.0	4.3	4.4	4.3	7.1	5.5

Normalized matrix

Option	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
t_1	0.330	0.227	0.305	0.467	0.331	0.451	0.512	0.381	0.286
t_2	0.409	0.370	0.382	0.381	0.374	0.442	0.465	0.338	0.479
t_3	0.266	0.411	0.525	0.465	0.388	0.414	0.261	0.358	0.367
t_4	0.301	0.405	0.285	0.336	0.515	0.227	0.284	0.363	0.501
t_5	0.240	0.397	0.532	0.362	0.223	0.502	0.435	0.324	0.282
t_6	0.552	0.299	0.257	0.323	0.442	0.235	0.333	0.447	0.292
t_7	0.447	0.482	0.237	0.269	0.298	0.268	0.269	0.419	0.372

The best and the worst value

f_j^* and f_j^- are the best positive ideal solution and the worst negative ideal solution for the j th criterion, respectively. By linking all f_j^*

together, an optimal combination is created that will give the highest score, which is the same for f_j^- as calculated in the table below.

Best-worst value matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
f_j^*	0.552	0.482	0.532	0.467	0.515	0.502	0.512	0.447	0.501

f_j^-	0.240	0.227	0.237	0.269	0.223	0.227	0.261	0.324	0.282
$f_j^* - f_j^-$	0.312	0.254	0.294	0.197	0.292	0.274	0.251	0.123	0.219

Weight of the criteria

Using the best-worst method, the weights of the criteria obtained from the previous phase have been calculated.

The distance between the options and the ideal solution

According to the equations described in the third chapter, the distance of the options from the ideal solution is calculated at this stage and presented in the following table:

Table 7.

Calculating the distance of options from the ideal solution

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	S(i)	R(i)
t_1	0.241	0.085	0.056	0.000	0.088	0.006	0.000	0.037	0.137	0.650	0.241
t_2	0.156	0.037	0.037	0.026	0.067	0.007	0.012	0.062	0.014	0.418	0.156
t_3	0.311	0.024	0.002	0.000	0.061	0.010	0.062	0.051	0.085	0.606	0.311
t_4	0.273	0.026	0.061	0.040	0.000	0.031	0.056	0.048	0.000	0.535	0.273
t_5	0.339	0.028	0.000	0.032	0.140	0.000	0.019	0.070	0.140	0.768	0.339
t_6	0.000	0.061	0.068	0.044	0.035	0.030	0.044	0.000	0.0133	0.415	0.133
t_7	0.114	0.000	0.073	0.060	0.104	0.026	0.060	0.016	0.082	0.535	0.114

VIKOR value and final ranking of options

The weight of the strategy of the majority agree with the criterion or maximum group

utility in this research is equal to 0.5. Hence, for different options, VIKOR values are according to the following table:

Calculation of VIKOR values

	t_1	t_2	t_3	t_4	t_5	t_6	t_7
Q(i)	0.615	0.097	0.709	0.522	1.000	0.043	0.170

Finally, considering the mentioned conditions, the final ranking of the options is

(the option with a lower value of VIKOR has a higher rating)

Final rank	Option	sign
1	Generation of electric energy from the combination of national grid and solar panels	t_6
2	generation of electricity from solar panels	t_2
3	Use of the national grid	t_7
4	Generation of electrical energy from storage batteries	t_4
5	Generation of solar electricity energy through joint investment	t_1
6	Generation of electric energy through gas generator	t_3
7	Generation of electricity from wind turbines	t_5

Figure 1. Final ranking of options

Results of solving mathematical model

In order to evaluate the efficiency of the presented model, an example according to real world conditions is presented and analyzed. An industrial center is considered here, which can use two different technologies for supplying electricity (both for supplying electricity for consumption and for supplying electricity for currency extraction). The first technology is the traditional method of receiving energy from

city grids. The second method is the result of building a solar energy generation site.

Consider also that technology 1: solar energy
Technology 2: urban grid

Energy 1: Electricity consumption

Energy 2: Electricity required for use in blockchain technology infrastructure

A numerical example with uncertain parameters is designed and analyzed in different scenarios to validate the robust model. The number of scenarios in this

example is 3 scenarios with probability of 20, 30 and 50% respectively.

Demand level of each energy			
	Scenario 1	Scenario 2	Scenario 3
Energy 1	90	95	100
Energy 2	75	69.4	65.2

The capacity to produce energy from any technology				
Energy	Technology	Scenario 1	Scenario 2	Scenario 3
1	1	75	85	70
1	2	1000	1000	1000
2	1	200	212.76	250
2	2	1000	1000	1000

Energy subscription of any technology				
Energy	Technology	Scenario 1	Scenario 2	Scenario 3
1	1	1000	1000	1000
1	2	2500	2700	2300
2	1	1000	1000	1000
2	2	2700	2500	2300

Energy subscription for any technology				
Energy	Technology	Scenario 1	Scenario 2	Scenario 3
1	1	6488500000	6458500000	6518500000
1	2	0	0	0
2	1	6902000000	6922000000	6852000000
2	2	0	0	0

The price of using each energy for each technology				
Energy	Technology	Scenario 1	Scenario 2	Scenario 3
1	1	280	300	250
1	2	1636	1532	1712
2	1	160	170	150
2	2	2435	2520	2312

The selling price of each energy from each technology				
Energy	Technology	Scenario 1	Scenario 2	Scenario 3
1	1	280	300	250
1	2	1636	1532	1712
2	1	160	170	150
2	2	2435	2520	2312

1	1	700	680	730
1	2	0	0	0
2	1	0	0	0
2	2	0	0	0

The following table presents the results of solving the problem with the help of the software:

System costs					
scenario	The fourth sentence	The third sentence	The second sentence	The first sentence	total cost
1	33942.57727	153888978.8	118381.8184	81707116.91	203613939.4
2	31795.78782	132476856.6	128792.8067	70838128.67	217359936.8
3	33547.11605	141308647	114385.1831	78709031.86	214004614.6

The following table shows the amount of cost created by each technology.

The amount of energy produced using technology				
		Scenario 3	Scenario 2	Scenario 1
Energy 1	Technology 1	51.602	50.815	51.219
Energy 1	Technology 2	43.991	44.009	44.267
Energy 2	Technology 1	68.921	66.438	67.017
Energy 2	Technology 2	.	.	.

According to the findings, the amount of city gas energy use in all scenarios is zero, which can be due to the large amount of greenhouse gas production. In the case of other productions, it can be seen that in each scenario, production quantities are more or less than the demand value, which can be considered due to the presence of response and model control variables. In fact, some of the production (surplus or shortage) is

included in the control variables so that it is possible to guarantee the model optimality and feasibility.

Comparing the results of certainty and uncertainty states

Here, the results of the third scenario (50 percent probability) are checked with the results of the first example so that the results of the certainty and uncertainty states values can be compared.

Comparison of the certainty and uncertainty results

		Scenario 3	Certainty
Energy 1	Technology 1	51.602	50.441
Energy 1	Technology 2	43.991	44.559
Energy 2	Technology 1	68.921	69.4
Energy 2	Technology 2	.	.

The findings show that in the third scenario, the absence of data causes the production of different amounts of energy. For instance, a smaller amount has been produced when using municipal electricity, but in the case of solar electricity, the production amount is slightly higher. In general, the demand has been slightly higher, which has been applied with a positive sign in the value of the control variable.

Summary and conclusion

The present research, with the aim of choosing the best methods of energy selection in industrial environments to supply consumed electricity as well as the necessary electricity to launch the infrastructure using blockchain technology, uses a hybrid approach based on the best-worst multi-criteria decision-making method and mathematical model under uncertainty

conditions. For this purpose, an auxiliary tool for managers is used in making final decisions, which initially chooses energy supply methods by using multi-criteria decision making approach. Then, optimization of the use level of various types of energy has been done using a mathematical model. As the results of solving the problem show, the criteria of "implementability", "productivity level" and "coordination with consumption pattern correction policies" are the most important in choosing the best option with weights of 0.339, 0.14 and 0.14, respectively. On the other hand, energy supply with the method of "electricity generation from the combined use of national grid and solar panels" has won the most points compared to other options. The solution of the relevant mathematical model shows that the use of solar panels to provide a significant part of the need for electrical energy has the highest economic efficiency. Considering that the solution time is affected by the growth of the problem dimensions, it is better to use powerful computer systems to solve the research problems, which, of course, are sometimes very difficult and expensive to access. Therefore, the use of exact solving algorithms can be efficient, and of course, considering the nature of the problem, which is among operational and planning level problems, the time to solve the problem can be ignored to some extent. In general, it can be said that the use of powerful computer systems and obtaining accurate results can be a priority in order to reach desired results.

References

- Guo, H. and X. Yu, A survey on blockchain technology and its security. *Blockchain: research and applications*, 2022. 3(2): p. 100067.
- Gad, A.G., et al., Emerging trends in blockchain technology and applications: A review and outlook. *Journal of King Saud University-Computer and Information Sciences*, 2022. 34(9): p. 6719-6742.
- Wang, Q. and M. Su, Integrating blockchain technology into the energy sector—from theory of blockchain to research and application of energy blockchain. *Computer Science Review*, 2020. 37: p. 100275.
- Alzoubi, Y.I. and A. Mishra, Green blockchain—A move towards sustainability. *Journal of Cleaner Production*, 2023. 430: p. 139541.
- Wang, Q., R. Li, and L. Zhan, Blockchain technology in the energy sector: From basic research to real world applications. *Computer Science Review*, 2021. 39: p. 100362.
- Sedlmeir, J., et al., The energy consumption of blockchain technology: Beyond myth. *Business & Information Systems Engineering*, 2020. 62(6): p. 599-608.
- Capponi, A., R. Jia, and Y. Wang, The evolution of blockchain: from lit to dark. *arXiv preprint arXiv:2202.05779*, 2022.
- UNCTAD, *Harnessing Blockchain for Sustainable Development: Prospects and Challenges*. 2021: UN.
- Sharif, A., et al., Analysis of the spillover effects between green economy, clean and dirty cryptocurrencies. *Energy Economics*, 2023. 120: p. 106594.
- Schulz, K. and M. Feist, Leveraging blockchain technology for innovative climate finance under the Green Climate Fund. *Earth System Governance*, 2021. 7: p. 100048.
- Vranken, H., Sustainability of bitcoin and blockchains. *Current opinion in environmental sustainability*, 2017. 28: p. 1-9.
- House, W., Climate and energy implications of crypto-assets in the united states. Accessed October, 2022. 21.
- Bada, A.O., et al. Towards a green blockchain: A review of consensus mechanisms and their energy consumption. in *2021 17th international conference on distributed computing in sensor systems (DCOSS)*. 2021. IEEE.
- Nygaard, A. and R. Silkoset, Sustainable development and greenwashing: How blockchain technology information can empower green consumers. *Business Strategy and the Environment*, 2023. 32(6): p. 3801-3813.
- Varavallo, G., et al., Traceability platform based on green blockchain: an application case study in dairy supply chain. *Sustainability*, 2022. 14(6): p. 3321.
- Bao, Z., et al., Towards green and efficient blockchain for energy trading: a non-cooperative game approach. *IEEE Internet of Things Journal*, 2023.
- Mohamed, S.K., et al., Blockchain technology adoption for improved environmental supply chain performance: The mediation effect of

- supply chain resilience, customer integration, and green customer information sharing. *Sustainability*, 2023. 15(10): p. 7909.
- Qin, M., et al., Blockchain market and green finance: The enablers of carbon neutrality in China. *Energy Economics*, 2023. 118: p. 106501.
- Polas, M.R.H., et al., Blockchain technology as a game changer for green innovation: Green entrepreneurship as a roadmap to green economic sustainability in Peru. *Journal of Open Innovation: Technology, Market, and Complexity*, 2022. 8(2): p. 62.
- Kontu, K., et al., Multicriteria evaluation of heating choices for a new sustainable residential area. *Energy and Buildings*, 2015. 93: p. 16.
- Štreimikienė, D., J. Šliogerienė, and Z. Turskis, Multi-criteria analysis of electricity generation technologies in Lithuania. *Renewable energy*, 2016. 85: p. 148-156.
- Al Garni, H., et al., A multicriteria decision making approach for evaluating renewable power generation sources in Saudi Arabia. *Sustainable energy technologies and assessments*, 2016. 16: p. 137-150.
- Çelikbilek, Y. and F. Tüysüz, An integrated grey based multi-criteria decision making approach for the evaluation of renewable energy sources. *Energy*, 2016. 115: p. 1246-1258.
- Jung, N., et al., Social acceptance of renewable energy technologies for buildings in the Helsinki Metropolitan Area of Finland. *Renewable energy*, 2016. 99: p. 813-824.
- Barragán, A., P. Arias, and J. Terrados, Renewable energy generation technologies on urban scale. *Renewable Energy and Power Quality*, 2017. 1.
- Talukdar, M.A., H. Rahman, and P.C. Sarker, Multi criteria decision analysis Algorithm based optimal selection of PV panel for grid-tie PV electricity generation system in context of dhaka, Bangladesh. *Life*, 2017. 5.
- Strantzali, E., K. Aravossis, and G.A. Livanos, Evaluation of future sustainable electricity generation alternatives: The case of a Greek island. *Renewable and sustainable energy reviews*, 2017. 76: p. 775-787.
- Kausika, B., O. Dolla, and W. Van Sark, Assessment of policy based residential solar PV potential using GIS-based multicriteria decision analysis: A case study of Apeldoorn, The Netherlands. *Energy Procedia*, 2017. 134: p. 110-120.
- Haddad, B., A. Liqid, and P. Ferreira, A multi-criteria approach to rank renewables for the Algerian electricity system. *Renewable energy*, 2017. 107: p. 462-472.
- Kumar, M. and C. Samuel, Selection of best renewable energy source by using VIKOR method. *Technology and Economics of Smart Grids and Sustainable Energy*, 2017. 2: p. 1-10.
- Wu, Y., et al., Social sustainability assessment of small hydropower with hesitant PROMETHEE method. *Sustainable cities and society*, 2017. 20: p. 522-537.
- Aboushal, E., Applying GIS Technology for optimum selection of Photovoltaic Panels "Spatially at Defined Urban Area in Alexandria, Egypt". *Alexandria engineering journal*, 2018. 57(4): p. 4167-4176.
- Rathore, N. and M. Singh. Selection of optimal renewable energy resources in uncertain environment using ARAS-Z methodology. in *2019 International Conference on Communication and Electronics Systems (ICCES)*. 2019. IEEE.
- Rani, P., et al., A novel approach to extended fuzzy TOPSIS based on new divergence measures for renewable energy sources selection. *Journal of Cleaner Production*, 2020. 257: p. 120352.
- Liu, J., et al., Selection of renewable energy alternatives for green blockchain investments: A hybrid IT2-based fuzzy modelling. *Archives of Computational Methods in Engineering*, 2021: p. 1-15.
- Rezaei, J., Best-worst multi-criteria decision-making method. *Omega*, 2015. 53: p. 49-57.
- Rezaei, J., Best-worst multi-criteria decision-making method: Some properties and a linear model. *Omega*, 2016. 64: p. 126-130.
- Opricovic, S., Multicriteria optimization of civil engineering systems. *Faculty of Civil Engineering, Belgrade*, 1998. 2(1): p. 5-21.
- Gupta, H., Evaluating service quality of airline industry using hybrid best worst method and VIKOR. *Journal of Air Transport Management*, 2018. 68: p. 35-47.