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Analyzing energy transition for industry 4.0-driven hybrid energy system selection with advanced neural network-used multi-criteria decision-making technique

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ABSTRACT

This study aims to select the appropriate renewable energy alternatives for the efficiency of hybrid energy systems to increase energy transition performance. For this purpose, a novel neural network (NN)-based fuzzy decision-making model is constructed that has three different stages. In the first stage, NN-based fuzzy decision matrix is created. Secondly, 6 different variables based on industry 4.0 are weighted with the sine trigonometric Pythagorean fuzzy entropy technique. Additionally, another calculation has been implemented with criteria importance through intercriteria correlation (CRITIC) to identify the consistency of the results. Furthermore, in the third stage, considering 5 different renewable energy alternatives, 10 different combinations are identified for hybrid energy systems. The most effective alternatives are defined by the sine trigonometric Pythagorean fuzzy ranking technique by geometric mean of similarity ratio to optimal solution (RATGOS) method. Moreover, to test the validity of these results, another analysis is conducted using the additive ratio assessment (ARAS) technique. The main contribution of the study is that the optimal renewable energy combination required for an efficient hybrid energy system is determined by performing a priority analysis between the variables. This situation has a significant guiding feature for investors. Similarly, the development of the RATGOS technique both increases the methodological originality of the study and enables more accurate alternative ranking. It is identified that the results of all methods are similar. Therefore, this situation gives information about the coherency and validity of the findings. It is concluded that the most important criterion is real-time capability. It is also denoted that the best combination for hybrid energy systems is Solar-Wind.

1. Introduction

Hybrid renewable energy systems play an important role to improve energy transition. These projects provide energy production by combining different clean energy sources. In this way, it is possible for this production process to be more stable. Similarly, hybrid systems also allow for more efficient energy consumption. The use of different renewable energy sources together also contributes to the increase in the reliability of this process. In this context, when electricity cannot be obtained from an energy source due to climatic conditions, the other energy source can support the production process. In this way, it is possible to obtain uninterrupted energy. Another advantage of these systems is that the efficiency in the energy production process can be increased [1]. Owing to the different types of clean energy designed on

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the site area, it is possible to reduce the initial cost of renewable energy investments. On the other hand, the establishment of a single storage system for different types of energy also contributes to reducing the costs in this process. Similarly, storing more energy also helps to increase the efficiency of the energy production process [2].

There are some issues that need to be considered to increase the performance of hybrid renewable energy investments. The high capacity of the energy storage system is an important issue in this process. In this way, a large amount of energy can be stored, thus contributing to uninterrupted energy production. Adequate technological infrastructure is another factor to be considered in this context. In this way, processes such as energy production and storage will be managed more effectively. Moreover, the maintenance of the projects should be done regularly [3]. In this way, it is possible to detect potential problems in the process early. This situation contributes both to the regular operation of the system and to the efficiency of the process. The financial analysis of the projects is another factor to be considered in this context. This helps to evaluate the profitability of investments. Furthermore, to ensure the effectiveness of these projects, the details in the legal regulations of the countries where the investments are made must be analyzed clearly [4].

It is necessary to integrate different energy sources correctly to increase the performance of hybrid renewable energy systems. In this way, it is possible to achieve efficiency in energy production processes. Otherwise, bringing together resources that are not very compatible with each other will not provide the expected effectiveness and efficiency. On the contrary, it increases the costs of energy investment projects and leads to a decrease in profitability. Therefore, for hybrid energy systems to be more effective, it is necessary to choose the right combination of renewable energy sources. In this context, to make this right choice, it is necessary to examine the factors affecting the performance of this process [5]. To achieve this goal, it is necessary to focus on the most important variables in this process. When the studies in the literature are examined, it is understood that although it is seen that the importance of these variables is focused on, there are a limited number of studies that identify the most important ones among these factors. Hence, there is a need for a new study in which the priority analysis of the variables in this process will be done [6].

Accordingly, in this study, it is aimed to select the right renewable energy alternatives to be integrated to ensure the efficiency of hybrid energy systems. In this framework, in the first stage, NN-based fuzzy decision matrix is created. After that, 6 different variables based on industry 4.0 are determined primarily. To determine the importance weights of these factors, an analysis is carried out with the sine trigonometric Pythagorean fuzzy entropy technique. Additionally, another calculation is made by taking into account the CRITIC method to determine the consistency of the results. On the other hand, considering 5 different renewable energy alternatives, 10 different combinations are determined for hybrid energy systems. The most effective of these different alternatives are identified by the sine trigonometric Pythagorean fuzzy RATGOS method. In addition, to test the validity of these results, another analysis is carried out using the ARAS technique.

The main contribution of this study is that an original fuzzy decision-making model is created to determine the optimal renewable energy combination required for an efficient hybrid energy system. In this proposed model, RATGOS methodology is considered to rank the alternatives. There are different models used to rank alternatives in the literature. However, these techniques have been criticized in many respects. Based on these criticisms, a new decision-making model was developed in this study that can rank using the geometric mean. This new model not only helps to eliminate criticism, but also allows ranking to be done more reliably. Another important superiority of this proposed model is that sine trigonometric Pythagorean fuzzy sets are taken into consideration. Owing to these sets, the defuzzification process can be applied in a more effective manner. This process has a powerful contribution to minimize uncertainties in the analysis process. Moreover, periodicity is considered in the analysis process. Hence, more effective findings can be reached.

Literature review is presented in the second part. The proposed methodology is explained in the third section. The results of this model are demonstrated in the fourth part. Discussion and conclusion are shown in the final sections.

2. Literature review

Hybrid renewable energy projects are of great importance in increasing energy transition performance. Under this heading, a literature review is carried out on the criteria that increase the performance of hybrid projects. In this context, a variable regarding this issue is taken into account in each paragraph. Technology represents the main driving force for successful hybrid energy integration. Hybrid energy systems combine different energy sources [7,8]. Accordingly, advanced technology is needed for this situation [9]. In addition, these systems require the management of variables from different energy sources. Therefore, advanced data analytics and technology are necessary to improve these systems [10]. Besides this, energy storage is an important issue for hybrid energy systems. Advanced technology is also required to provide efficiency in the energy storage system [11]. Liu et al. [12] examined the main performance indicators of hybrid energy harvesting technologies. For hybrid energy integration, technology has an important place. Alonso et al. [13] conducted a study that included a techno-economic evaluation of hybrid energy storage systems consisting of hydrogen and batteries. They underlined the necessity of advanced technology in hybrid energy systems. Ismail et al. [14] used multi-criteria decision-making techniques to understand the main indicators of these systems in Egypt. Accordingly, it is stated that technological improvement plays a crucial role in the performance improvements of hybrid energy systems.

One of the important criteria for the hybrid energy integration to be successful is the cost. In addition to the many advantages of hybrid systems, initial investment costs are also quite high [15]. Since hybrid systems cover more than one energy system, operating and maintenance costs can be higher [16]. However, with the help of the established system, the costs of energy cuts can be avoided. In addition, hybrid systems are likely to provide long-term return on investment (Mughami and Mutanbara, 2023). Ibrahim et al. [17] conducted a study on the development of a demand-side energy management system for hybrid energy sources. It is emphasized that costs are important for the success of hybrid energy systems. Ali et al. [18] carried out a study on the energy storage techno-economic evaluation for hybrid energy sources. The importance of costs for the sustainability of hybrid energy systems is emphasized. Nazari-Heris and Asadi [19] actualized a study to provide energy to houses with hybrid energy systems. It is defined that the cost factor is important for these systems to be sustainable and effective. Furthermore, Sambhi et al. [20] stated that the cost factor is important in the hybrid energy production system produced with hydrogen.

Functionality is one of the important criteria affecting the issue of energy integration. The main purpose of energy integration is to ensure that businesses are efficient, sustainable, and competitive [21]. Accordingly, the hybrid energy types to be used must be functional [22]. In addition, having a structure that can keep up with the developing technology will positively affect the integration [11]. Apart from this, it is possible to respond more easily to seasonal fluctuations and sudden demand changes owing to the functional structure [23]. Rasool et al. [24] carried out a comparative evaluation of the multi-objective optimization of the hybrid energy storage system. In the study, the importance of functionality in hybrid energy use is mentioned. Shi et al. [25] investigated the optimal management of electrical and heat energies in a hybrid energy system. They reached a conclusion that higher functionality will lead to ease of energy conversion and lower energy losses. Mariasiu and Kelemen [26] conducted a study on the efficiency of the hybrid energy storage system for electric vehicles. They underlined the significance of the functionality as well as high efficiency. Hylla et al. [27] studied hybrid energy storage techniques and emphasized that it is necessary to provide functionality to improve the effectiveness of this system.

Another important aspect affecting hybrid energy integration is organizational effectiveness. Organizational effectiveness is a concept that expresses the extent to which businesses reach their goals and how efficiently they manage business processes [28]. Accordingly, the inspections to be made in the energy integration process and the early resolution of possible errors gain importance [29]. In addition, being able to respond quickly to customer demands will facilitate the process [30]. While doing all these, qualified personnel are needed because these personnel will facilitate these processes [31]. Martinez et al. [32] conducted a study to evaluate the new service development process of renewable energy investments. In this process, the importance of organizational effectiveness is emphasized. Mehmood et al. [33] carried out a study examining digitalization, renewable energy use, and technological innovation in G8 countries. They identified that organizational effectiveness should be provided for the performance improvements of the hybrid systems. Karamoozian et al. [34] examined the risk assessment of renewable energy projects with fuzzy multi-criteria decision-making techniques. They determined that organizational effectiveness plays a significant role to increase the effectiveness of these systems.

As a result of the literature review, the following conclusions can be identified. First, hybrid energy system provides many important benefits, such as increasing efficiency and effectiveness in the energy storage process. Due to this situation, the popularity of this subject increased in the literature especially in the last years. The scholars mainly focused on the significance of these systems. However, there are very limited studies in which the main indicators are identified. Therefore, the main missing part in the literature is that there is a strong need to conduct a priority analysis for this situation. To satisfy this need, the aim of our study is to determine the most appropriate hybrid energy integration strategies by conducting a priority analysis for the indicators.

3. Methodology

In this study, the optimal renewable energy combination required for an efficient hybrid energy system is determined by performing a priority analysis between the variables. This situation has a significant guiding feature for investors. In this way, it will be possible to increase the efficiency and productivity of the projects. This makes a strong contribution to increasing the profitability of investments. In this section, information about the models is given. Entropy and CRITIC methods are used to determine the weights of the criteria. The biggest advantage of the Entropy technique compared to other similar methods is that it performs an objective analysis. This technique is based entirely on data and is not affected by subjective judgments. In this way, it is possible to obtain more accurate analysis results. On the other hand, there is a subjective evaluation in techniques such as AHP and ANP. Determining the factors affecting the effectiveness of hybrid energy projects is of key importance. Therefore, entropy is the most optimal method in the analysis process of these criteria.

Then, the best alternative is identified by RATGOS and ARAS methods. Most of the ranking techniques in the literature, such as VIKOR and TOPSIS are criticized due to some reason [35]. RATGOS technique is introduced to overcome these criticisms. The main advantage of this new technique is the consideration of the geometric mean in the analysis process. Hence, it can be possible to reach more appropriate ranking results. In this study, considering 5 different renewable energy alternatives, 10 different combinations are determined for hybrid energy systems. Ranking of these alternatives is one of the most significant steps for this proposed model. Based on this evaluation, investment strategies will be presented to the investors. Hence, the effectiveness of the selected model is vital in this process. Considering these issues, choosing the RATGOS technique contributes to achieving more accurate results.

Sine trigonometric Pythagorean fuzzy numbers are preferred in the analysis made with these methods [36]. Since sine trigonometric numbers do not have a linear structure, they take the sine curve into account. This especially enables the defuzzification process to be carried out more effectively. This enables the uncertainty in the process to be reduced. The uncertainty problem is one of the most important problems in multi-criteria decision-making analysis. The main reason for this is that the problems have a very complex structure. Therefore, it is possible to reduce this problem by choosing sine trigonometric numbers in the proposed model. In this way, more successful results can be achieved. The steps of the analysis process are summarized in Fig. 1.

The details of the steps are presented under subtitles.

3.1. Creating NN-based decision matrix

In methods based on expert opinion, giving equal importance regardless of the experts' experiences is criticized in the literature. The important level of an expert with 16 years of experience is not equal to that of an expert with 8 years of experience. In other words, the relationship between experience and knowledge level is not linear. For this purpose, NN systems are used to add a non-linear knowledge level factor. The steps of this process are demonstrated as follows.

Step 1: NN system is built, and machine learning is performed.

The implementation of the NN system has been realized through programming in the Python language, utilizing the Keras and TensorFlow libraries. These libraries play a pivotal role in configuring the neural network layers and specifying activation functions. In the scope of this research, the NN system is composed of a comprehensive structure with a total of 9 layers, among which 7 are designated as hidden layers [37]. The activation function employed for the hidden layers is the sigmoid function. This choice is grounded in the sigmoid function's capability to map values within the interval of 0–1, aligning seamlessly with the intrinsic structure of fuzzy logic. The sigmoid function is denoted in Equation (1).

$$S(x)=\frac{1}{1+e^{-ax}} \tag{1}$$

In Equation (1), the parameter a signifies the slope of the function, while e represents the mathematical constant known as Euler's number. The input variable of the model is structured as a dual-component system, comprising expert opinions and the experience period. In accordance with the sine trigonometric Pythagorean number, the output layer of the model is designed, representing membership and non-membership values. The Adam algorithm is employed for the computation of weights between these layers. This algorithm is chosen for its computational efficiency, particularly when dealing with relatively small datasets [38]. The calculations for the Adam algorithm are provided between Equations (2)–(6).

$$W_{t+1}=W_t-\frac{a}{\sqrt{\widehat{S}_t+\epsilon}}\widehat{V}_t \tag{2}$$

$$\widehat{V}_t=\frac{V_t}{1-\beta_1^t} \tag{3}$$

$$\widehat{S}_t=\frac{S_t}{1-\beta_2^t} \tag{4}$$

$$V_t=\beta_1 V_{t-1}+(1-\beta_1)\frac{\partial L}{\partial w_t} \tag{5}$$

$$S_t=\beta_2 S_{t-1}+(1-\beta_2)\left[\frac{\partial L}{\partial w_t}\right]^2 \tag{6}$$

In this context, a demonstrates learning coefficient, w gives information about the weight, β indicates the degree to which past gradients are involved in the process and $\frac{\partial L}{\partial w_t}$ refers to the gradient. S and V are the

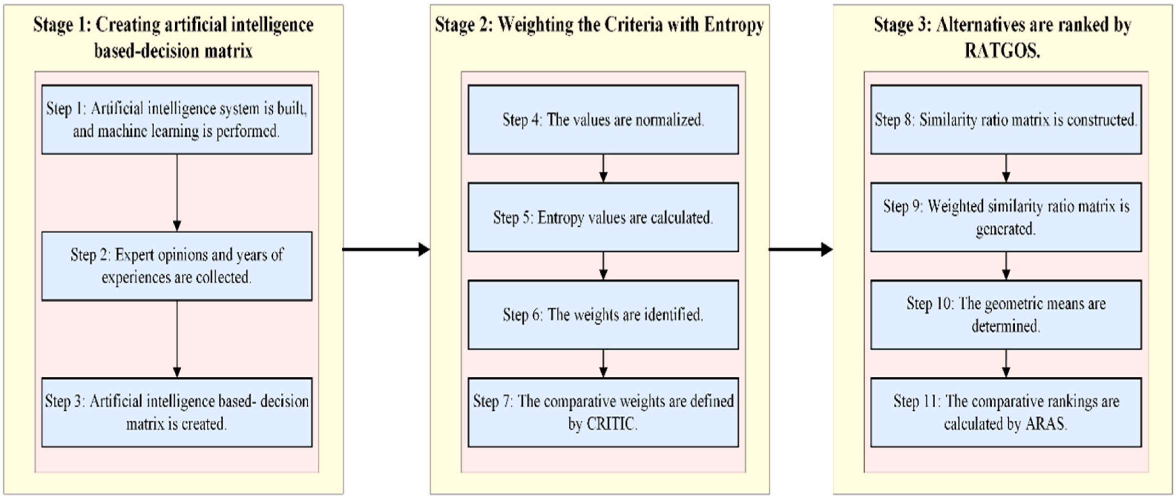

Fig. 1. Flowchart.

Table 1
Linguistic variables.

Linguistic Term	Score	Fuzzy Numbers	
		$\sin\left(\frac{\pi}{2}\mu\right)$	$\sqrt{1-\sin^2\left(\frac{\pi}{2}\sqrt{1-\nu^2}\right)}$
Lowest	1	0.2334	0.5136
Low	2	0.3827	0.3716
Moderately Low	3	0.5225	0.2651
Normal	4	0.7071	0.1187
Moderately High	5	0.8526	0.0702
Influential	6	0.9239	0.0353
Perfect	7	0.9724	0.0126

initial values for solution. Following the mathematical modelling of the NN system, a dataset is generated for the purpose of machine learning. The training data set is created randomly from expert opinions and experience periods using the simulation technique. The output variable is subsequently formulated using Equations (7) and (8) based on the input variables derived from the simulation. The values in Table 1 are considered when converting expert opinions into fuzzy numbers.

$$STPFWA=\left(\sqrt{1-\prod_{i=1}^{n}\left(1-\sin^2\left(\frac{\pi}{2}\mu_i\right)\right)^{w_i}},\prod_{i=1}^{n}\left(\sqrt{1-\sin^2\left(\frac{\pi}{2}\sqrt{1-\nu_i^2}\right)}\right)^{w_i}\right) \tag{7}$$

$$w_i=\frac{d_i}{\sum_{i=1}^{n}d_i} \tag{8}$$

In this context, d in the equations refers to the experience periods of the experts. Also, μ indicates the membership value and ν refers to the non-membership value of Pythagorean fuzzy number. The values in Table 1 are considered when converting expert opinions into fuzzy numbers.

Machine learning fits of a model between the input and output variables. The learning process is carried out iteratively to ensure the adequacy of the NN system. The fitness of the model is evaluated by considering the mean squared error, as defined in Equation (9). The iteration continues until the value of the mean squared error approaches zero. As the number of repetitions exhibits marginal reductions beyond a certain threshold, the number of epochs is consequently set to 100.

$$MSE=\frac{1}{m}\sum_{i=1}^{m}(Y_i-\widehat{Y}_i)^2 \tag{9}$$

In this process, Y represents the actual value and $\widehat{Y}$ is the output value of the model. The implementation of the NN system serves the purpose of mitigating the issue of assigning equal importance to expert opinions. To circumvent the potential pitfalls associated with linear weighting, a non-linear and intricate system is created. This approach is designed to enhance the objective of analyses in the context of multi-criteria decision-making processes.

Step 2: Expert opinions and years of experiences are collected.

A team of experts is formed with three people who have sufficient experience in this area. The members of the team evaluate alternatives based on criteria. It makes the evaluation according to the linguistic expressions in Table 1. Additionally, the experience of the experts is considered.

Step 3: NN based-decision matrix is created.

Expert opinions and experience periods are given as input to the NN system. After that, the fuzzy decision matrix (A) is formed as in Equation (10). Within this scope, μ is the membership value while ν defines the non-membership value.

$$A=\begin{bmatrix}\left(\sin\left(\frac{\pi}{2}\mu_{11}\right),\sqrt{1-\sin^2\left(\frac{\pi}{2}\sqrt{1-\nu_{11}^2}\right)}\right) & \cdots & \left(\sin\left(\frac{\pi}{2}\mu_{1n}\right),\sqrt{1-\sin^2\left(\frac{\pi}{2}\sqrt{1-\nu_{1n}^2}\right)}\right)\\ \vdots & \ddots & \vdots \\ \left(\sin\left(\frac{\pi}{2}\mu_{m1}\right),\sqrt{1-\sin^2\left(\frac{\pi}{2}\sqrt{1-\nu_{m1}^2}\right)}\right) & \cdots & \left(\sin\left(\frac{\pi}{2}\mu_{mn}\right),\sqrt{1-\sin^2\left(\frac{\pi}{2}\sqrt{1-\nu_{mn}^2}\right)}\right)\end{bmatrix} \tag{10}$$

3.2. Sine trigonometric Pythagorean fuzzy entropy

Entropy method is the objective multi-criteria decision-making method used to weighting of the criteria. This method takes into account the uncertainty measure in the decision matrix for the weighting process. The steps of the Entropy method with sine trigonometric Pythagorean fuzzy numbers are given below [23].

Step 4: The values are normalized.

First, the matrix A is normalized. The normalized matrix (R) is calculated by Equation (11).

$$r_{ij} = \begin{cases} \left(\sin\left(\frac{\pi}{2}\mu_{ij}\right), \sqrt{1-\sin^2\left(\frac{\pi}{2}\sqrt{1-v_{ij}^2}\right)}\right) & \textit{for benefit criteria} \\ \left(\sqrt{1-\sin^2\left(\frac{\pi}{2}\sqrt{1-v_{ij}^2}\right)}, \sin\left(\frac{\pi}{2}\mu_{ij}\right)\right) & \textit{for cost criteria} \end{cases} \tag{11}$$

Step 5: Entropy values are calculated.

The entropy value (E) of each criterion is calculated by Equation (12).

$$E_j = \frac{1}{(\sqrt{2}-1)m}\sum_{i=1}^{m}\left(\sin\left(\frac{\pi}{4}\left(1+\mu_{ij}^2-v_{ij}^2\right)\right)+\sin\left(\frac{\pi}{4}\left(1-\mu_{ij}^2+v_{ij}^2\right)\right)-1\right) \tag{12}$$

Step 6: The weights are identified.

Finally, the weights of criteria ($\boldsymbol{w}$) are obtained with Equation (13).

$$w_j = \frac{1-E_j}{n-\sum_{j=1}^{n}E_j} \tag{13}$$

3.3. Sine trigonometric Pythagorean fuzzy CRITIC

CRITIC considers the correlation between the criteria in the decision matrix. The steps of the CRITIC method with sine trigonometric Pythagorean fuzzy numbers are given below [39].

Step 7: The comparative weights are defined by CRITIC.

First, A matrix is defuzzified by Equation (14).

$$S(\sin p) = \sin^2\left(\frac{\pi}{2}\mu_p\right) - \left(\sqrt{1-\sin^2\left(\frac{\pi}{2}\sqrt{1-v_p^2}\right)}\right)^2 \tag{14}$$

Defuzzified matrix of A is normalized with Equation (15). The normalized matrix (B) is given in Equation (16).

$$b_{ij} = \begin{cases} \frac{x-min}{max-min} & \textit{for benefit criteria} \\ \frac{max-x}{max-min} & \textit{for cost criteria} \end{cases} \tag{15}$$

$$B = \begin{array}{c} \\ A1 \\ \vdots \\ Am \end{array} \begin{array}{c} \begin{array}{ccc} C1 & \dots & Cn \end{array} \\ \begin{bmatrix} b_{11} & \cdots & b_{1n} \\ \vdots & \ddots & \vdots \\ b_{m1} & \cdots & b_{mn} \end{bmatrix} \end{array} \tag{16}$$

The correlation matrix (ρ) is defined with the help of Equation (17).

$$\tilde{\rho}_{jk} = \sum_{i=1}^{m}\left(\tilde{b}_{ij}-\tilde{\bar{b}}_j\right)\left(\tilde{b}_{ik}-\tilde{\bar{b}}_k\right) \Big/ \sqrt{\sum_{i=1}^{m}\left(\tilde{b}_{ij}-\tilde{\bar{b}}_j\right)^2\sum_{i=1}^{m}\left(\tilde{b}_{ik}-\tilde{\bar{b}}_k\right)^2} \tag{17}$$

The standard deviation (σ) of each criterion is calculated by Equation (18).

$$\tilde{\sigma}_j = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(\tilde{b}_{ij}-\tilde{\bar{b}}_j\right)^2} \quad i=1,2,\dots,m \tag{18}$$

Index values (C) are computed by Equation (19).

$$\tilde{C}_j = \tilde{\sigma}_j\sum_{k=1}^{n}\left(1-\tilde{\rho}_{jk}\right) \quad j=1,2,\dots,n \tag{19}$$

Finally, weights ($\boldsymbol{w}$) are identified with Equation (20).

$$\tilde{w}_j = \frac{\tilde{C}_j}{\sum_{j=1}^{n}\tilde{C}_j} \tag{20}$$

3.4. Sine trigonometric Pythagorean fuzzy RATGOS

RATGOS is a newly method in the literature for ranking alternatives. In this method, the geometrical similarity ratios of the alternatives to the optimal value are calculated. The steps of the RATGOS method with sine trigonometric Pythagorean fuzzy numbers are given below [40].

Step 8: Similarity ratio matrix is constructed.

First, A matrix is defuzzified by Equation (14). Next, optimal values are determined with Equations (21) and (22).

$$optimal = \max a_i \quad \textit{for benefit criteria} \tag{21}$$

$$optimal = \max\frac{1}{a_i} \quad \textit{for cost criteria} \tag{22}$$

Each criterion is divided by the optimal value with the help of Equations (23) and (24). Thus, the similarity ratio matrix (N) is calculated.

$$N = \frac{A}{optimal} \quad \textit{for benefit criteria} \tag{23}$$

$$N = \frac{optimal}{A} \quad \textit{for cost criteria} \tag{24}$$

Step 9: Weighted similarity ratio matrix is generated.

The weighted similarity ratio matrix (Z) is obtained by multiplying with the weights by Equation (25). In this scope, w values are the weights of the criteria.

$$Z = wN \tag{25}$$

Step 10: The geometric means are determined.

The average similarity ratio is calculated by taking the geometric mean (G) of the weighted similarity ratios of each alternative by Equation (26).

$$G_i = \sqrt[n]{\prod_{j=1}^{n}z_{ij}} \tag{26}$$

3.5. Sine trigonometric Pythagorean fuzzy ARAS

ARAS is used to determine the best alternative. The steps of the ARAS method with sine trigonometric Pythagorean fuzzy numbers are given below [41].

Step 11: The comparative rankings are calculated by ARAS.

First, optimal values in A matrix are obtained by Equation (27).

$$optimal = \{a_i | \max(S(A_i))\} \tag{27}$$

The values in matrix A and the optimal values are multiplied by the weights with Equations (28) and (29). Thus, a weighted matrix (F) is obtained where λ denotes a scale.

$$F = wA \tag{28}$$

$$\lambda \sin p_1 = \left(\sqrt{1 - \left(1 - \sin^2\left(\frac{\pi}{2}\mu_1\right)\right)^{\lambda}}, \left(\sqrt{1 - \sin^2\left(\frac{\pi}{2}\sqrt{1 - v_1^2}\right)} \right)^{\lambda} \right) \tag{29}$$

The F matrix is defuzzified by Equation (14). Then, the sums of the optimal solution and alternatives (M) are taken by Equations (30) and (31).

$$M_j = \sum S(F_i) \tag{30}$$

$$\sin p_1 \bigoplus \sin p_2 = \left(\sqrt{1 - \left(1 - \sin^2\left(\frac{\pi}{2}\mu_1\right)\right)\left(1 - \sin^2\left(\frac{\pi}{2}\mu_2\right)\right)}, \sqrt{1 - \sin^2\left(\frac{\pi}{2}\sqrt{1 - v_1^2}\right)} \sqrt{1 - \sin^2\left(\frac{\pi}{2}\sqrt{1 - v_2^2}\right)} \right) \tag{31}$$

Finally, the Q values are calculated by dividing the M values by the optimal sum (M_0) with the help of Equation (32). The larger Q value is considered as the best optimal value.

$$Q_i = \frac{M_i}{M_0} \tag{32}$$

4. Analysis results

In this section, firstly, criteria are defined based on industry 4.0 perspectives. Industry 4.0 aims to bring production processes more efficiently with the combination of current technologies such as data analysis and NN. Therefore, it is possible to increase the performance of hybrid renewable energy investments by selecting the criteria created with this point of view. For example, more effective data analysis can be done by considering industry 4.0 factors. This allows hybrid energy systems to be planned more accurately. On the other hand, thanks to the more active use of NN, the efficiency of energy storage systems can be increased.

These factors are defined as interoperability, virtualization, independent management, real-time capability, service orientation and modularity. Interoperability means that two or more parties, machine or human, can exchange content perfectly [42]. In other words, in the field of IoT, interoperability in the communication protocol between sensor and actuator devices can allow the integration of industrial applications with IoT-based devices [43]. Interoperability includes new ways to manage machines, data, and components, while coexisting new data and formats with old ones [44]. In this way, it is accepted that interoperability by providing the connection between machines and people is the main advantage of industry 4.0 [45].

While virtualization is used for process monitoring and machine-to-machine communication, it shows that devices can monitor physical process [46]. The aim of virtualization is to create a virtual copy of a production system to predict, analyze or simulate the behavior of the system in real time [47]. In addition, thanks to virtualization, a large number of application services and network services that run on traditionally dedicated servers and devices can be moved to commodity hardware as virtual services [48]. The transition from centralization to decentralization can be considered as an important design principle of Industry 4.0, and the principle of independent management brings about changes in all kinds of activities, including decision-making, relations between stakeholders and the type of organizational structure [49]. As a matter of fact, while independent management expresses the ability of the system to make its own decisions thanks to the cyber-physical system, it also helps effective globalization without any central planning [50].

Real-time capability means that analysis can be taken in real time and instantly at any point. This allows one to look at what has happened, what can be changed, and where productivity prospects lie, while the goal is to process and analyze data to continually optimize company operations [51]. While one of the main goals of Industry 4.0 is to increase the variability of production processes and reduce the additional cost for products, a service-oriented manufacturing architecture can achieve this goal [52]. The service orientation mentioned here refers to the shift from products to the use of data to create new services that are more responsive to changing market needs [53]. In other words, service orientation requires devices to be able to meet the needs of users through the internet of the service [46].

Step 1: NN system is built, and machine learning is performed.

In Python, the NN model is built with the activation function given in Equation (1) and the optimization algorithm given in Equations (2)–(6). Moreover, the sigmoid function is taken into account in this model to ensure activation within neurons. Sigmoid function is a mathematical function that can convert input values into output in the range of 0–1 and resembles an S curve. In this way, it is possible to keep the values in the analysis process within certain limits. Because of this advantage, the sigmoid function makes it possible to adapt the values produced in neurons in this model to the fuzzy logic rules. In the analyzes carried out with fuzzy numbers, membership and non-membership values of these numbers are defined between 0 and 1. Due to this similarity, the sigmoid function appears to be very suitable for analyzes with fuzzy numbers [54,55]. In other words, compared to the advantages of similar activation functions, the sigmoid function has some advantages [56]. Due to these advantages, in this model the sigmoid function is integrated into the fuzzy decision-making analysis process.Sigmoid function is preferred as the activation function that best suits the structure of the output variable. In this way, the output is obtained in accordance with the definition of fuzzy numbers. Afterwards, machine learning is performed with 1000 simulation data. Simulation data is partition into train, validation, and test to calculate and test the model's parameters. For this purpose, 30 % of the data is reserved for testing. In this way, the learning success of the NN model is tested with test data. Similar success can also be achieved in test data as in train data. Cross validation is ensured by the high success rate of the two statues. Additionally, to test the parameters of the model, the validation dataset is randomly partition by 20 %.

Moreover, 9 layers and sigmoid activation function are preferred in the construction of the NN model. Layers are structures created to establish a mathematical connection between input values and output values. At the same time, one of the reasons for creating layers is to create non-linear connections between input and output [57]. In this way, the importance weights of experts will not be linearly affected by changes in demographic factors. This situation also contributes to the determination of more accurate expert weights. The number of layers in the analysis process is taken into account in different ways in the literature [58]. The biggest problem with choosing a very high number of layers is that it increases the complexity in the process. Similarly, in analyzes made with a high layer number, efficiency decreases as the number of operations increases. In summary, it is very critical to achieve correct analysis results by selecting a reasonable number of layers. In this context, this number is determined as 9 in a significant part of the studies in the literature [59–61]. Taking this into consideration, the number of layers in this proposed model is selected as 9.

On the other hand, different number of neurons is selected in each layer. Neuron is an intra-layer computational module that performs different operations in each layer. In this context, the large number of neurons allows different computational weights to be taken into account [62]. Thus, it is possible to take different conditions into account during the analysis process. This supports achieving more effective and realistic analysis results. Taking these issues into consideration, in this study, the number of neurons in each layer is determined as 8, 4, 2, 4, 2, 16, 8, 8, 2, respectively. In this process, the powers of 2 are generally preferred in terms of neuron numbers. The reason for this condition is that neuron numbers are determined this way in many studies in the literature [62–64]. Moreover, these neuron numbers are selected differently to increase or decrease linearity and complexity. In this context, during the analysis process in this study, the number of neurons is first determined as 8 and then reduced to 2 in the other layers. Within this framework, first high and then low uncertainty issues are taken into account [64]. On the other hand, this number is increased to 16 in later layers. Thus, the model is created taking into consideration the issues where complexity and linearity increase greatly. In this way, it is aimed to make the analysis results more accurate [65].

Furthermore, sensitivity analysis of the selected layers and neuron numbers is also performed. In this context, the consistency of the figures selected in this study is checked. In this context, the number of layers is changed between 5 and 15. Similarly, the number of neurons in each new layer takes different values as a power of 2. In this way, it is tested whether the analysis results change under different conditions. According to the model success results obtained, it is understood that the MSE values are similar. According to these results, the change in the number of layers does not cause serious differences in the results. This gives information that the number of layers selected in the model is reasonable and consistent. Similarly, this aspect demonstrates the consistency and reliability of the number of neurons selected in the model. The details of MSE values based on different layers are demonstrated in Fig. 2.

In the machine learning process, the output variable is obtained by Equations (7) and (8). The learning process of NN is carried out iteratively. In other words, machine learning parameters are calculated from the data with 100 epochs. For learning success, the MSE value in Equation (9) is calculated. In this process, we used simulation data to create a model. In this context, the Monte-Carlo simulation technique is taken into account. This technique is taken into consideration in the literature to increase data during the analysis process of many studies [66–68]. Therefore, this technique is used in the process of increasing the number of data in the proposed model. Simulation data is divided into 3 parts: train, validation, and test. Dividing the data set into 3 is one of the frequently used methods to test the success and validity of NN models [69,70]. In this way, the model is prevented from memorizing [71]. Additionally, the consistency of the results can be tested when the model encounters data other than the train data. Train and validation data are used in the construction of the model. At each epoch step, the parameters of the model are calculated from the train data and checked with validation. The success of the model in each epoch is calculated by MSE values. At the end of the 100 epoch steps, the MSE value for validation is calculated as 0.00402. Afterwards, the model is analyzed with test data. The MSE value between the output produced by the model for the test data and the actual output value is determined as 0.0040117. Since these values are close to 0, it is stated that the learning is successful.

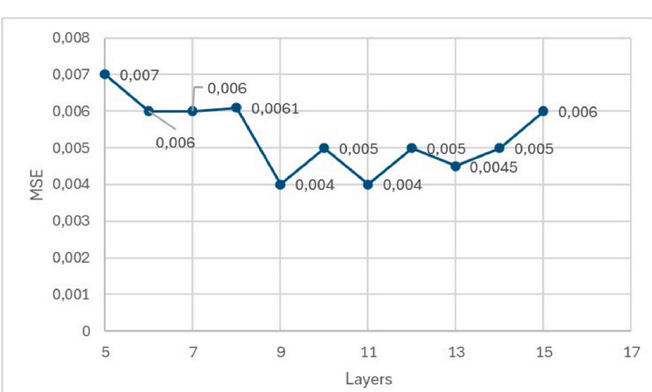

Fig. 2. MSE values for different layers.

Step 2: Expert opinions and years of experiences are collected.

Modularity contributes to better use of Industry 4.0 technologies in the processing of a wide variety of components. This approach aims to design more products with fewer components using “modules” that can be integrated into several different products [72]. In short, under the principle of modularity, Industry 4.0 ensures that complex value chains such as smart factories and distribution networks have the necessary physical and managerial flexibility to deal with environmental turbulence, and this principle results in improved production efficiency [73]. On the other side, by considering 5 different renewable energy alternatives, 10 different combinations are determined for hybrid energy systems. An expert team consisting of 3 people is established. Experts evaluate hybrid energy types with the values in Table 1. The team members consist of experts with experience in their fields and academic studies. Experts’ experience periods are 15, 18 and 17 years. These people work as senior managers in international energy companies. All of these people have master’s degrees. These people have also managed a wide range of projects in energy storage, renewable energy technologies and hybrid energy projects. The evaluations are denoted in Table 2.

Step 3: NN based-decision matrix is created.

Expert opinions and team members’ experiences in Table 2 are given as input variables of the NN system. As a result of the evaluation of the NN system, a sine trigonometric Pythagorean fuzzy decision matrix is obtained. The decision matrix in Equation (10) is given in Table 3.

4.1. Weighting the criteria with sine trigonometric Pythagorean fuzzy entropy

In this subsection, the steps of criteria weighting are defined as follows.

Step 4: The values are normalized.

First, the importance weights and orderings of the criteria are calculated. Thus, decision matrix is normalized with Equation (11). All criteria are benefits.

Step 5: Entropy values are calculated.

After, Entropy values (E) are calculated with Equation (12).

Table 2
Expert opinions.

Expert 1	Interoperability	Virtualization	Independent	Real-Time	Orientation	Modularity
Solar-Wind	6	7	6	7	6	6
Solar-Hydro	3	6	3	7	2	3
Solar-Biomass	2	6	1	6	1	3
Solar-Geothermal	4	7	2	6	2	1
Wind-Hydro	2	6	4	7	3	2
Wind-Biomass	1	6	2	7	3	2
Wind-Geothermal	1	7	1	6	1	2
Hydro-Biomass	2	6	3	7	1	2
Hydro-Geothermal	3	6	2	6	4	1
Biomass-Geothermal	3	6	1	7	2	2

Expert 2	Interoperability	Virtualization	Independent	Real-Time	Orientation	Modularity
Solar-Wind	5	7	5	7	5	6
Solar-Hydro	2	6	2	7	3	2
Solar-Biomass	1	7	1	6	1	2
Solar-Geothermal	2	7	2	6	3	2
Wind-Hydro	2	6	3	7	3	1
Wind-Biomass	2	6	2	7	2	3
Wind-Geothermal	3	7	2	6	2	2
Hydro-Biomass	1	6	1	7	2	3
Hydro-Geothermal	2	6	2	6	2	2
Biomass-Geothermal	3	6	2	7	2	1

Expert 3	Interoperability	Virtualization	Independent	Real-Time	Orientation	Modularity
Solar-Wind	5	7	5	7	6	6
Solar-Hydro	1	7	1	6	3	3
Solar-Biomass	1	6	2	6	2	2
Solar-Geothermal	2	6	1	6	3	1
Wind-Hydro	1	7	3	7	2	2
Wind-Biomass	2	6	1	6	3	1
Wind-Geothermal	2	7	2	6	3	3
Hydro-Biomass	2	6	3	7	3	2
Hydro-Geothermal	1	7	3	7	1	2
Biomass-Geothermal	2	6	2	7	2	1

Table 3
Decision matrix.

	Interoperability		Virtualization		Independent		Real-Time		Orientation		Modularity	
Solar-Wind	0.87	0.07	0.87	0.07	0.87	0.07	0.87	0.07	0.87	0.07	0.87	0.07
Solar-Hydro	0.55	0.27	0.87	0.07	0.55	0.27	0.87	0.07	0.84	0.09	0.84	0.09
Solar-Biomass	0.42	0.39	0.87	0.07	0.42	0.38	0.87	0.07	0.42	0.38	0.75	0.14
Solar-Geothermal	0.83	0.09	0.87	0.07	0.45	0.35	0.87	0.07	0.84	0.09	0.42	0.38
Wind-Hydro	0.45	0.35	0.87	0.07	0.87	0.07	0.87	0.07	0.84	0.09	0.45	0.35
Wind-Biomass	0.46	0.34	0.87	0.07	0.45	0.35	0.87	0.07	0.84	0.09	0.57	0.25
Wind-Geothermal	0.59	0.24	0.87	0.07	0.46	0.34	0.87	0.07	0.59	0.24	0.76	0.13
Hydro-Biomass	0.45	0.35	0.87	0.07	0.71	0.16	0.87	0.07	0.59	0.24	0.77	0.13
Hydro-Geothermal	0.55	0.27	0.87	0.07	0.76	0.13	0.87	0.07	0.74	0.14	0.46	0.34
Biomass-Geothermal	0.84	0.09	0.87	0.07	0.46	0.34	0.87	0.07	0.57	0.25	0.42	0.39

Table 4
Entropy values and weights.

Criteria	Entropy Values	Weights	Rank
Interoperability	0.8198	0.02972	6
Virtualization	0.4113	0.09707	2
Independent	0.8190	0.02984	5
Real-Time	0.4112	0.09709	1
Orientation	0.6868	0.05164	3
Modularity	0.7870	0.03512	4

According to the result of the Entropy method, the most important criterion is real-time capability because of the highest weight (0.09709). The second most critical factor is virtualization since the weight value of this criterion is 0.09707.

Step 6: The weights are identified.

The weightings of the criteria are calculated by Equation (13). Entropy values and weights are given in Table 4.

4.2. Comparison of the results with sine trigonometric Pythagorean fuzzy CRITIC

The weighting results of the criteria are compared by using CRITIC technique in this subsection.

Step 7: The comparative weights are defined by CRITIC.

The results of the weights obtained by the sine trigonometric Pythagorean fuzzy Entropy method are compared with the sine

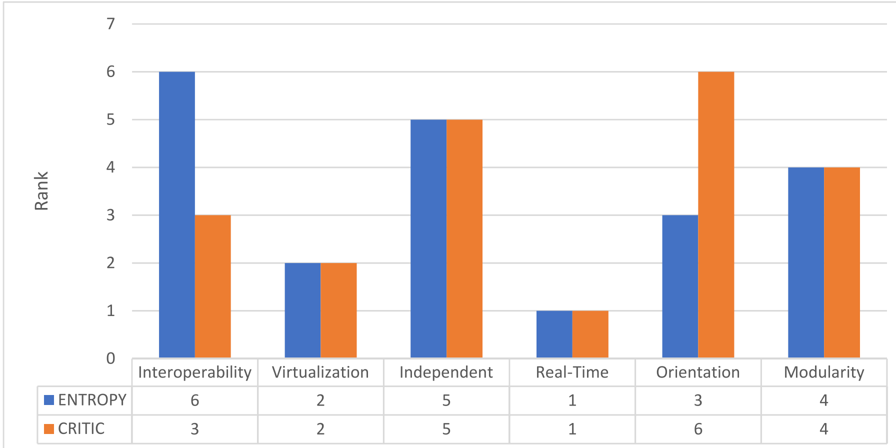

Fig. 3. Results of two weighting methods.

Table 5
N matrix.

Alternatives	Interoperability	Virtualization	Independent	Real-Time	Orientation	Modularity
Solar-Wind	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Solar-Hydro	−0.4635	1.0000	−0.4635	0.9987	0.8238	0.7855
Solar-Biomass	−0.8910	0.9965	−0.8813	0.9987	−0.8801	0.3412
Solar-Geothermal	0.7735	0.9987	−0.7908	0.9987	0.8238	−0.8830
Wind-Hydro	−0.7908	1.0000	0.9687	1.0000	0.8180	−0.7940
Wind-Biomass	−0.7585	0.9987	−0.7908	0.9987	0.7844	−0.3888
Wind-Geothermal	−0.3205	1.0000	−0.7585	0.9987	−0.3176	0.3823
Hydro-Biomass	−0.7940	0.9987	0.1693	1.0000	−0.3176	0.4396
Hydro-Geothermal	−0.4635	1.0000	0.3823	1.0000	0.2882	−0.7585
Biomass-Geothermal	0.8191	0.9987	−0.7585	1.0000	−0.3904	−0.8910

trigonometric Pythagorean fuzzy CRITIC technique. The decision matrix in Table 3 is used in this process. The weights of criteria are calculated by considering Equations (14) and (20). The results of the two methods are demonstrated in Fig. 3.

According to Fig. 2, it is seen that the results of the two methods are similar. Therefore, this situation gives information about the coherency of the findings.

4.3. Ranking the alternatives with sine trigonometric Pythagorean fuzzy RATGOS

Secondly, the most optimal alternative is determined by considering the criteria using sine trigonometric Pythagorean fuzzy RATGOS.

Step 8: Similarity ratio matrix is constructed.

Similarity ratio matrix is calculated with Equations (21) and (22) using the decision matrix in Table 3. The *N* matrix is given in Table 5.

Table 7
G values and ranking.

Alternatives	G	Rank
Solar-Wind	0.0563	1
Solar-Hydro	0.0226	9
Solar-Biomass	0.0384	2
Solar-Geothermal	0.0252	8
Wind-Hydro	0.0163	10
Wind-Biomass	0.0288	5
Wind-Geothermal	0.0329	4
Hydro-Biomass	0.0279	6
Hydro-Geothermal	0.0278	7
Biomass-Geothermal	0.0344	3

According to Tables 7 and it is denoted that the best combination for hybrid energy systems is Solar-Wind. Solar-Biomass, Biomass-Geothermal and Wind-Geothermal are other successful combinations in this framework.

Table 6
Weighted similarity ratio matrix.

Alternatives	Interoperability	Virtualization	Independent	Real-Time	Orientation	Modularity
Solar-Wind	0.02972	0.09707	0.02984	0.09709	0.05164	0.03512
Solar-Hydro	−0.01377	0.09707	−0.01383	0.09696	0.04254	0.02759
Solar-Biomass	−0.02648	0.09673	−0.02629	0.09696	−0.04545	0.01198
Solar-Geothermal	0.02299	0.09695	−0.02359	0.09696	0.04254	−0.03102
Wind-Hydro	−0.02350	0.09707	0.02890	0.09709	0.04224	−0.02789
Wind-Biomass	−0.02254	0.09694	−0.02359	0.09696	0.04051	−0.01366
Wind-Geothermal	−0.00952	0.09707	−0.02263	0.09696	−0.01640	0.01343
Hydro-Biomass	−0.02360	0.09694	0.00505	0.09709	−0.01640	0.01544
Hydro-Geothermal	−0.01377	0.09707	0.01141	0.09709	0.01488	−0.02664
Biomass-Geothermal	0.02434	0.09694	−0.02263	0.09709	−0.02016	−0.03130

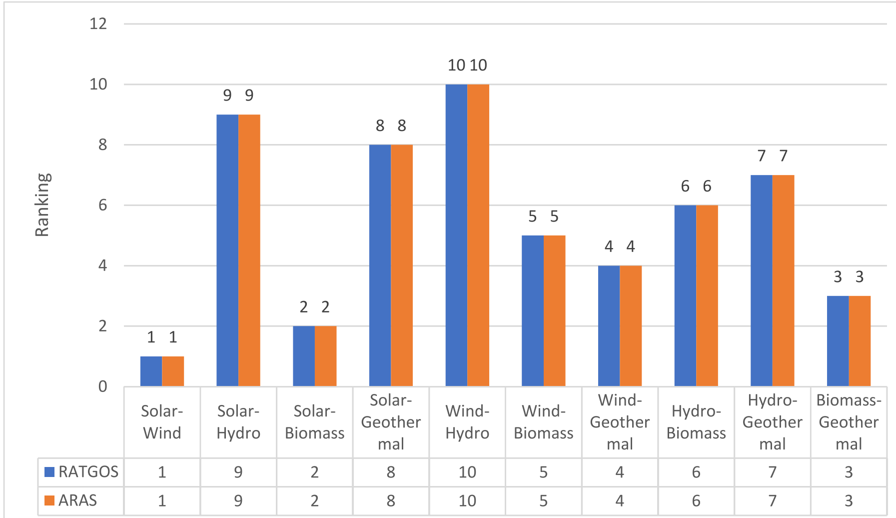

Fig. 4. Results of two ranking methods.

Step 9: Weighted similarity ratio matrix is generated.

Weighted similarity ratio matrix is obtained by using Equation (25). The values in Table 4 are used as weights. Weighted similarity ratio matrix is given in Table 6.

Step 10: The geometric means are determined.

Then, G values are calculated with the help of Equation (26). The G values and ranking of the alternatives are shown in Table 7.

4.4. Comparison of the results with the STPFY-ARAS

Alternatives are also ranked by sine trigonometric Pythagorean fuzzy ARAS.

Step 11: The comparative rankings are calculated by ARAS.

Equations (27)–(32) are taken into consideration for this situation. The results of these two methods are indicated in Fig. 4.

Fig. 4 denotes that the results of the two methods are similar. This situation underlines that the findings of the proposed model are reliable and valid.

4.5. Sensitivity analysis

For the consistency of the results of the ranking models, the results are tested with different weight values. In this way, it is determined how sensitive the ranking of alternatives is to the criterion weights. The rankings of RATGOS and ARAS methods against five different situations are shown in Fig. 5.

According to Fig. 4, the rankings of hybrid renewable energy alternatives are consistent, as the two methods give the same results at different weights. In other words, the results are generalizable regardless of methods and weights.

5. Discussion

Real-time capability has been identified as the most important industry 4.0 factor in selecting the right hybrid energy systems. This situation gives the information that the energy production processes should be monitored instantly. In this way, the obtained data can be analyzed effectively. According to Amir et al. [74], this allows quick decisions to be made to solve potential problems. Thus, it is possible to manage hybrid energy systems more effectively. Li et al. [75] stated that to increase the performance of hybrid energy systems, energy storage processes must operate effectively. Thanks to the real-time capability, automation systems can be used in this process. This contributes

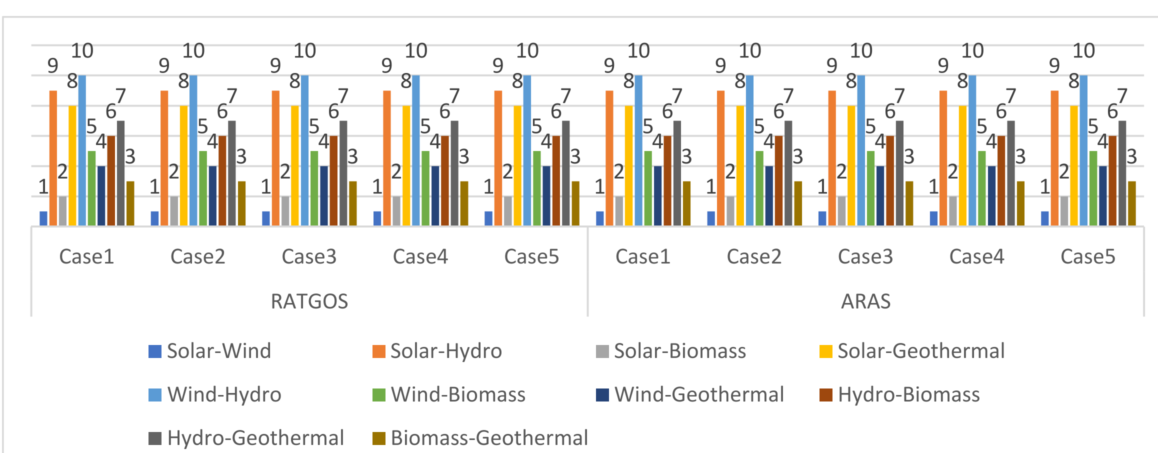

Fig. 5. The result of sensitivity analysis.

significantly to increasing the performance of the energy storage process. Moreover, thanks to the real-time analysis of the data, possible errors can be detected quickly. Thus, it is possible to minimize problems such as power cuts in hybrid energy systems. On the other hand, Kheshti et al. [76] concluded that with real-time capability, differences between energy production and consumption can be detected quickly. In this way, it is much more possible to achieve the balance between these issues by taking the necessary precautions.

Virtualization is also a factor that should be taken into account to determine the right combination in hybrid renewable energy projects. In this perspective, it is aimed to create the same physical systems that exist in reality in a digital environment. This may positively affect the performance of hybrid renewable energy projects. Thanks to this system, renewable energy systems to be developed can be simulated in a virtual environment. Belouda and Mami [77] defined that this issue provides information on how different types of energy can be best integrated. Thus, it is possible to increase the performance of hybrid energy systems. On the other hand, Hussenet and Boucetta [78] identified that optimization of energy production and distribution systems can be achieved thanks to virtual simulations. This situation contributes to significantly reducing energy costs. Virtualization also allows early detection of problems encountered during the process. In this way, the necessary measures can be taken in a timely manner and disruptions in energy production processes can be prevented.

It is determined that the hybrid use of wind and solar energy is the most optimal combination. The most important benefit provided by this combination is ensuring continuity in the energy production process. Both of these energies can be obtained in different climatic conditions. In other words, while electricity can be produced from wind turbines when there is a lot of wind, solar panels also allow electricity to be generated on sunny days when there is no wind. Therefore, it is possible to obtain uninterrupted energy by using these two types of energy in a hybrid way. Roy et al. [79] concluded that this condition helps projects to work more effectively. The most important disadvantage of renewable energy types compared to fossil fuels and nuclear energy is that there are interruptions in the energy production process due to climate differences. In this context, management of this disadvantage can be easier by using solar and wind energy together. According to Yang et al. [80] and Akarsu and Genç [81], this issue gives renewable energy projects a significant competitive advantage compared to others.

Hybrid renewable energy projects play an important role in the energy transition process. Hybrid systems provide more stable energy production by combining different energy sources. This situation contributes to ensuring the balance of energy supply and demand [82]. On the other hand, hybrid systems also help increase energy efficiency. More efficient energy use enables more effective use of energy resources and can reduce energy costs [23]. This situation seriously supports increasing the success of the energy transition. One of the most important advantages of hybrid energy systems is that they diversify energy production [83]. This provides a significant opportunity to obtain uninterrupted energy. Thus, energy costs will decrease, and it may be possible to prefer renewable energy more [84]. Thus, energy transition processes can be carried out more effectively [85]. Moreover, by combining different renewable energy sources, the costs of energy storage systems can be reduced. In this case, the financial performance of clean energy projects can be increased [86]. Thus, a more successful energy transition is possible.

6. Conclusion

This study tries to select the appropriate renewable energy alternatives to be integrated to ensure the efficiency of hybrid energy systems. For this purpose, in the first stage, NN-based fuzzy decision matrix is created. Next, 6 different variables based on industry 4.0 are selected. For the calculation of the weights of these factors, an evaluation is conducted with the sine trigonometric Pythagorean fuzzy entropy technique. Furthermore, another calculation is performed by CRITIC method to determine the consistency of the results. Additionally, considering 5 different renewable energy alternatives, 10 different combinations are identified for hybrid energy systems. The most effective alternatives are defined by the sine trigonometric Pythagorean fuzzy RATGOS method. Moreover, to test the validity of these results, another analysis is conducted using the ARAS technique. It is determined that the results of all methods are similar. Therefore, this situation gives information about the coherency and validity of the findings. It is concluded that the most important criterion is real-time capability. It is also denoted that the best combination for hybrid energy systems is Solar-Wind.

Real-time capability plays the most critical role for the effectiveness of the hybrid energy systems. Based on these analysis results, it can be possible to identify some policy implications. Smart grid infrastructure should be strengthened for real-time monitoring and control of hybrid energy systems. In this way, it may be easier to optimize energy storage processes. On the other hand, artificial intelligence approaches should be included in these projects. Thanks to the analyzes carried out with these new technologies, it is possible to make more accurate predictions regarding energy production and consumption. In addition to them, one of the biggest disadvantages of renewable energy projects is that they are affected by climate differences. To minimize this problem, energy storage technologies need to be developed. To achieve this goal, it is important to increase research and development studies. Government incentives are also key to increasing this research. In particular, incentives such as tax exemptions contribute to reducing costs. Thus, it becomes more possible to increase these studies.

The main contribution of the study is that the optimal renewable energy combination required for an efficient hybrid energy system is determined by performing a priority analysis between the variables. This situation has a significant guiding feature for investors. Similarly, the development of the RATGOS technique both increases the methodological originality of the study and enables more accurate alternative ranking. The main limitation of the study is that a country groups is not evaluated. Instead of this situation, the results are presented in a general manner. However, the leading indicators and appropriate combinations can change for different countries. Due to this condition, it is strongly recommended that in the future studies, developing countries can be examined. Energy independence plays a crucial role for the economic improvements of these countries. Therefore, specific strategies should be presented for them to increase effectiveness in clean energy projects.

CRediT authorship contribution statement

Peide Liu: Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Serkan Eti:** Writing – original draft, Resources, Investigation, Formal analysis, Conceptualization. **Serhat Yüksel:** Writing – review & editing, Validation, Resources, Investigation, Conceptualization. **Hasan Dinçer:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Investigation, Conceptualization. **Yaşar Gökalp:** Writing – review & editing, Visualization, Validation, Software, Resources. **Edanur Ergün:** Writing – review & editing, Visualization, Resources, Investigation, Conceptualization. **Ahmet Faruk Aysan:** Writing – review & editing, Validation, Software, Investigation.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Casey Canfield reports financial support was provided by Alfred P Sloan Foundation. co-author serves in uncompensated advisory role for the Green-e Governance Board - J. H.

Abbreviation

AHP Analytical Hierarchy Process
ANP Analytical Network Process
ARAS Additive Ratio Assessment
CRITIC Criteria Importance Through Intercriteria Correlation
RATGOS Ranking Technique by Geometric Mean of Similarity Ratio to Optimal Solution

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