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# Application of Fuzzy Logic Techniques in Solar Energy Systems: A Review

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**Abstract**

Fuzzy logic has been applied to a wide range of problems, including process control, object recognition, image and signal processing, prediction, classification, decision-making, optimization, and time series analysis. These apply to solar energy systems. Though experts in renewable energy prefer fuzzy logic techniques, their contribution to the decision-making process of solar energy systems lies in the possibility of illustrating risk factors and introducing the concepts of linguistic variables of data from solar energy applications. In solar energy systems, the primary beneficiaries and audience of the fuzzy logic techniques are solar energy policy makers, as it concerns decision-making models, ranking of criteria or weights, and assessment of the potential location of the installation of solar energy plants, depending on the case. In a real-world scenario, fuzzy logic allows easy and efficient controller configuration in a non-linear control system, such as a solar panel. This study attempts to review the role and contribution of fuzzy logic in solar energy based on its applications. The findings from the review revealed that the fuzzy logic application identifies and detects faults in solar energy systems as well as in the optimization of energy output and the location of solar energy plants. In addition, fuzzy model (predicting), hybrid model (simulating performance), and multi-criteria decision-making (MCDM) are components of fuzzy logic techniques. As the review indicated, these are useful as a solution to the challenges of solar energy systems. Importantly, the integration and incorporation of fuzzy logic and neural networks should be recommended for the efficient and effective performance of solar energy systems.

**Keywords:** decision making; renewable energy; uncertainty; fuzzy model; neural network

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## 1. Introduction

Energy is vital for every country. The increase in population has increased energy use and consumption [1]. Due to the depletion rate of fossil fuels, many researchers have identified renewable energy-based systems. Fossil fuels include coal, peat, oil, and uranium ore. Also, when burned, they release carbon dioxide, contributing to global warming and the greenhouse effect [2]. Among fossil fuels, oil and coal are used for electricity generation, lighting, heating, and cooling. Global warming, which is a worldwide phenomenon, is the result of the use of fossil fuels. Using fossil fuels also produces greenhouse gases such as methane, carbon dioxide, and nitrous oxide [3]. Renewable energy is environmentally friendly; about 16% of global energy consumption comes from renewable energy. Its sources are natural resources or processes from which energy is obtained and which are inexhaustible or renewable faster than consumed. They do not cause any greenhouse gases or carbon dioxide. Renewable energy is also cost-efficient and is from limitless resources, implying it can be used repeatedly. Examples of renewable energies include solar, wind, hydro, tidal, geothermal, and biomass [4].

Renewable energy sources have been used for many years, even in ancient times. Still, due to the discovery of fossil fuels, they lost ground in the 19th and 20th centuries, with the majority being used for heating and transportation [1]. Due to the depletion of fossil fuels and the negative impact on the environment, in the late 20th century, renewable energy sources have become much more widely used. They can be produced by collecting different energy forms from other sources [1]. Hence, they are vital in sustainable development and face the problem of depletion of non-renewable and limited resources. These energy sources are considered "clean", and their use contributes to energy stability, stability in energy supply, which is essential to situations of energy crises [5]. Renewable energy is being applied in science and technology, from automobiles to industrial and thermal power plants. In the past decade, renewable energy has been used in automobiles (bikes, cars, etc.), replacing fossil fuels with solar energy and electricity; this represents sustainable development [1]. Hence, they are the best option for eliminating fossil fuels, which are limited and harm the environment.

In briefly discussing examples of renewable energy sources, as mentioned earlier, solar energy is defined as the radiant ionization energy emitted by the sun. It is one of the highly used energies [6]. Two types of solar energy systems are commonly implemented in developing and developed countries: photovoltaic (PV) and solar thermal energy. PV energy is one of the preferred solar energy technologies and acts as a prospective energy source for the future [7]. In 2021, it supplied approximately 2% of the global electricity demand [8]. Examples of PV technologies include multi-junction solar cells, concentrator photovoltaic systems, hot-carrier converters, floating PV power generation, and down conversion of high-energy photons [9].

On the other hand, solar thermal energy is produced by converting radiation energy into thermal energy [10]. Solar thermal energy technologies include the solar heating of water and air, solar cooking, and concentrating solar power (CSP). Wind energy is considered the second most preferred renewable energy source for electricity generation [11], and it is converted into electricity by wind turbine-based power plants. There are two types: the onshore wind farms (installed on land) and the offshore wind farms (installed at sea or freshwater) [12]. Wind energy depends on wind, and the location of the wind farms depends on the yearly average speed of wind, which should be enough to generate the estimated power [9]. For bioenergy, this originates from biomass sourced either by modern methods or traditional methods [13], and it contributes to the heating, transport sector, and the generation of environmentally friendly electricity [14]. The modern bioenergy is used in generating heat and electricity with the products of biogas, biochar, and biodiesel through different thermal conversion technologies such as gasification, carbonization, torrefaction, combustion, and pyrolysis. At the same time, in the traditional method, it comes from agricultural materials such as charcoal, crop residues, fuelwood, and animal secretion [15]. Hydropower is also known as hydroelectric power (hydraulic power). The electrical energy is generated from the harvested energy of moving water, contributing 20 per cent of electricity generation worldwide. Compared to other renewable energy sources, hydropower has the highest conversion efficiency, about 90%, for generating electricity [16]. There are various types of hydropower, including pumped storage systems, cascaded reservoir hydropower plants, and small hydropower plants. Another example of renewable energy is tidal energy, which is produced by converting kinetic energy from the tidal stream into electrical energy [17] and is produced by the difference in height between two water bodies [18]. There are two types of tidal energy: hydrokinetic and oscillating water columns. Finally, geothermal energy is the thermal energy from the radioactive decay of mineral resources and the primitive structure of the Earth [19]. Geothermal energy is rich and inexhaustible inside the Earth compared to other renewable energy sources [20], it is naturally stable, and it has no carbon dioxide emissions [21]. There are two types of geothermal power plants, which are binary power cycles (organic Rankine cycles) and steam power cycles [22]. Most of these geothermal plants are built near their resources (usually not more than 10 km) to reduce heat loss of the geothermal energy in thermally insulated pipelines [23].

Having looked at the general overview of the need for renewable energy, applications, sources, and their examples and technologies, the fuzzy logic techniques of one of the sources of renewable energy technologies need to be conducted. In this case, solar energy is considered in the study because of its abundance, sustainability, and increasing cost effectiveness compared to other renewable energy technologies. Therefore, it is at the forefront of renewable energy. Previous studies on this fuzzy logic technique have been conducted primarily focusing on the general renewable energy sources [24], hybrid studies [25], specific applications of solar energy, such as solar panels [26], solar radiation [27], grid, and standalone solar energy [28]. However, an existing study that covers all the examples of solar energy technologies about the fuzzy logic technique remains unclear, mainly as it concerns reducing uncertainty and enhancing decision-making processes. Therefore, the review aimed to provide a representative development of the description of the fuzzy logic concept concerning solar energy systems and their application. To contribute to academic knowledge, the review provides concise, comprehensive, and detailed information through a rigorous review process. Thus, the significant contribution of the evaluation is as follows:

- To provide existing applications of various fuzzy logic techniques on solar energy technologies, thereby identifying their advantages and disadvantages.
- To provide an extension and combination of other models with fuzzy logic to address the limitations of selection and the decision-making of solar energy systems.
- To reveal the capability that enhances the reliability of results based on fuzzy logic techniques in solving complex problems associated with solar energy systems.
- To propose a recommendation for a suitable fuzzy logic technique to reduce the uncertainty in solar energy processes, based on the literature.

With the authors' contribution in the present study, the structured review starts with a general description of solar energy technologies, thereby focusing on various existing models used in the literature in relation to the technology. The overview of fuzzy logic techniques, detailing its classification in solar energy systems applications and previous studies on the application of fuzzy logic techniques in solar energy systems, was presented. The review also looked at the solar energy challenges with possible solutions via fuzzy logic technique and, finally, concluded with the limitations, future directions, and recommendations of the study. All these were considered in the study to answer the following research questions:

- Are there existing models for solar energy technologies aside from the fuzzy logic techniques?
- What are the existing fuzzy logic techniques used in the solar energy industries for modelling, optimization, and prediction capability?
- In what ways are the applications of fuzzy logic techniques compared with other conventional methods?
- Can fuzzy logic enhance the efficiency of solar energy processes and decision-making under uncertainties?
- Are fuzzy logic techniques capable of addressing the challenges of solar energy systems?

## 2. Methodologies

The review used Science Direct, Scopus, Web of Science, and renewable energy reports as databases. Using a Boolean operator and adhering to the criteria of each database, the fundamental short phrases utilized to investigate the data from these databases combine the same terms. Keywords include application AND fuzzy logic technique OR model AND solar energy AND technology OR system OR process. These keywords or concepts were employed to find pertinent research and literature from peer-reviewed publications. This was not constrained by the search time; therefore, coverage was examined from the beginning of the fuzzy logic model in 1965 until 30 April 2025. The study considered book chapters, review articles, and original articles. Interestingly, publications containing specific keywords in the topic, abstract, contributors, and keywords are included in the search results. Considering the inclusion and exclusion criteria is a standard requirement when designing high-quality research. Inclusion criteria are the key features that the researcher employed in the study, whereas the exclusion criteria are defined as the features that were not employed in the study, thereby interfering with the success of the study [29]. The inclusion and exclusion criteria of the study are presented in Table 1. This is related to the study conducted by Zenani et al. [30].

**Table 1.** Selection of data based on criteria [Adopted from Zenani et al. [30].

| Study Inclusion Criteria | Study Exclusion Criteria |
|---|---|
| Scholarly published contributions in the form of original articles, review papers, book chapters from peer-reviewed journals, and energy reports | Published contributions outside the original articles, review papers, book chapters from peer-reviewed journals, and energy reports are excluded. |
| Time span of 1965–2025 | Outside the time span of 1965–2025 |
| Only publications written in the English language are included | Publications written in non-English languages are excluded |
| The type of publication considered is a narrative (literature) review article | Not any other review as publication type (systematic review, etc.) |

In Table 1, the literature was identified using publication contributions from original articles, review papers, book chapters, and energy reports. This is necessary to build and have a solid foundation of the topic knowledge and identify the research gaps, thereby contextualizing the authors' own work. Only publications in the English language were included. The reason for this is that English is known as the international language of science, and it leads to more and better citations. Therefore, it achieves a global reach and an international audience. The date of publication was restricted from 1965 (to state and recognize the first publication on fuzzy logic technique) onward, to identify the most up-to-date literature. The type of publication considered is review articles because they are flexible and less time consuming than other types of reviews, such as the systematic review, which was an exclusion criterion. Having established that, the exclusion criteria focus on and deal with other criteria features outside and in addition to inclusion, and this has the tendency to affect the results of the study. It is interesting to mention that the references are up to date and current, making them relevant to the topic. The reference lists of each included article were searched manually to obtain the potentially eligible articles. This was performed by screening titles and abstracts of retrieved articles to exclude articles that are irrelevant to the review. Thereafter, the full texts of the potentially relevant papers were reviewed further to examine their eligibility with reference to the Smela et al. [31] study.

## 3. Solar Energy Briefly

Solar energy is the renewable energy that can be obtained from the Sun, and it reaches the Earth in various forms of heat and light. It is used in generating electricity, desalinating water, and generating heat, etc. [32]. Among the other renewable energies, solar energy could be the best option for the future since it is the most abundant renewable energy source [33]. Further, solar energy is the best option for the future because it is inexhaustible, giving solid and increasing output efficiencies that other renewable energy sources do not [34]. The energy source is not harmful to the ecosystem, which means the natural balance is kept consistent for the betterment of the living organisms [35]. As mentioned previously, solar energy has two main types, which are photovoltaic energy (PV) and solar thermal energy. There are various PV technologies, which include concentrated photovoltaic (CPV) systems, multi-junction solar cells (MJSC), floating PV (FPV) power generation, down conversion of high-energy photons, photovoltaic thermal systems, and hot-carrier converters.

CPV is a technique for focusing the solar light on a PV receiver, using concentrating optics on a small area of solar cells, and its purpose is to collect beam radiation and scattered radiation, which are then focused on the solar cells [36]. The CPV has three types, which are low concentration, medium concentration, and high concentration, which are based on the factor of concentration [37]. The high-concentration photovoltaics have the highest efficiency, so they have the most potential [38]; however, the low-concentration photovoltaics are more critical due to high tracker tolerance, low cost of manufacturing, and passive heat sinks [39]. The main types of CPV are parabolic dish, quantum dot, Fresnel lens, parabolic trough, compound parabolic, and non-imaging dish concentrators [40]. These types can be classified into low concentration and high concentration. Under high concentration, it is a parabolic dish, a non-imaging dish, and a Fresnel lens; then under low concentration, it is a parabolic trough, a quantum dot, and a compound parabolic [40].

To increase the efficiency of solar energy conversion, multi-junction solar cells (MJSC), sometimes called tandem cells, comprise several semiconductor sub-cells stacked and connected in series [41]. Because of their high optical transparency and low electrical resistance, interconnectors usually use Esaki interbond tunnel diodes to prevent current blockage between sub-cells [42]. With Indium Gallium Phosphide (InGaP)/Indium Gallium Arsenic (InGaAs)/Germanium (Ge) materials, the maximum efficiency for MJSCs ever recorded is 40.7% [43]. Selecting the right materials for the top cell is essential; InGaP is favoured over AlGaAs because of its superior interface qualities, low oxygen sensitivity, and compatibility with Ge or GaAs [44]. The InGaAs increases open-circuit voltage and short-circuit current when paired with Ge; it is perfect for the middle sub-cell [45]. Ge works well as the bottom cell for absorbing longer wavelengths due to its low bandgap [46].

Using floating platforms, like pontoons or rafts, floating photovoltaic (FPV) systems are solar-powered and are installed on water surfaces like lakes, ponds, and reservoirs [47]. FPVs, which are widely used in nations like China, Brazil, Italy, Japan, and the United States [48], use traditional PV arrays but also benefit from the water's natural cooling, which reduces overheating and slightly increases energy efficiency [49]. Both parties gain from FPV systems; the water surface helps cool the solar panels, improving performance, decreasing water evaporation, and preventing algal growth [50]. Furthermore, FPVs preserve land and encourage sustainable land use without posing environmental issues because they are situated on bodies of water [51]. The most extensive FPV system in the world, the Saemangeum system in Korea, which spans 30 $km^2$ and produces 2.1 GW of electricity, is a noteworthy example [52].

By splitting high-energy photons, which are typically wasted in traditional solar cells, into two lower-energy photons, down conversion allows for creating multiple electron–

hole pairs per original photon, increasing solar-cell efficiency [53]. A photoluminescent converter, which divides high-energy photons into two useful lower-energy photons, is positioned in front of the solar cell in this procedure [54]. Vos et al. [55] claim that photons with energies higher than twice the band gap (2Eg) can be used more efficiently in the converter through radiative transitions, involving impurity levels, or between the valence and conduction bands. Through this technique, solar-cell efficiency can be increased by about 39.63% [56].

Solar energy is converted into electrical and thermal energy simultaneously by photovoltaic thermal (PV/T) systems, which combine solar cells and solar collectors [57]. PV/T systems use this excess heat, increasing overall efficiency, in contrast to conventional PV systems [58], which only convert about 20% of solar radiation into electricity and waste the remainder as heat [59]. The solar collector in PV/T aids in absorbing and reusing the heat, preserving electrical performance, as solar cell efficiency declines with increasing temperature. Utilizing a glazing cover to direct sunlight onto the PV cells, the system transforms some of the radiation into electricity and the remainder into heat, which is then collected by a fluid-based collector. The PV/T systems provide a cost-effective dual energy solution and perform noticeably better than standalone PV or thermal units.

Advanced solar cells called hot-carrier converters are made to use extra photon energy [60], which is typically lost as heat in traditional solar cells, to produce more electricity. Conventional solar cells use energy transitions between the valence and conduction bands, but thermal loss usually wastes any photon energy above the bandgap [61]. To address this, hot-carrier converters slow down the cooling of photo-excited carriers, giving high-energy carriers more time to contribute to the production of electricity [62]. This method can greatly increase solar conversion efficiency, surpassing that of traditional photovoltaic cells by up to 65% [63]. Converting solar radiation into heat is known as solar thermal energy (STE), and it is frequently utilized for power generation, industrial process heat, and home space or water heating [10]. Three different types of collectors, low, medium, and high temperature, are used in this technology to capture solar energy using a fluid underneath a receiver [64]. Applications such as pool and home heating use low/medium collectors, which are usually flat plates. The main purpose of high-temperature collectors, which employ mirrors or lenses, is to generate electricity. STE has a higher energy conversion efficiency than photovoltaic (PV) systems because it can absorb more than 90% of solar radiation [65].

## 4. Studies on Various Models Used in Solar Energy Technology

Planning at every level, whether global, national, or regional, is crucial for managing energy use and its environmental effects. Researchers, policymakers, and industrialists must collaborate in creating energy models that will help in sustainable development and decrease the production of greenhouse gases and carbon dioxide. Most modelling methods are used for forecasting and planning, such as time series, regression analysis, ARIMA, and artificial intelligence techniques, including neural networks, fuzzy logic, and genetic algorithms. These models assist in evaluating energy supply, economic elements, emissions, technology, and public acceptance.

Mellit et al. [66] presented four applications of machine learning and deep learning algorithms for PV systems. These applications covered the modelling and estimation of PV power, forecasting of PV output power for a PV plant, and fault classification of a PV string, which is solved by Fuzzy Logic, k-Nearest Neighbours (k-NNs), deep neural networks (DNNs), long short-term memory (LSTM), and multilayer perceptron (MLP). To use the listed algorithms, knowledge of MATLAB or Simulink was required. Kumari et al. [67] published a review article on solar irradiance forecasting models based on deep learning.

The deep learning models used are long short-term memory (LSTM), recurrent neural network (RNN), deep neural network (DNN), dynamic Bayesian network (DBN), echo state network (ESN), and convolutional neural network (CNN). Kazem et al. [68] reviewed the algorithm models, thereby describing, evaluating, and comparing most of the software (photovoltaic system simulation programme (PVSS) software, SOLSTOR software, SOLCEL software, SolarPro software, clean power estimator (CPE) software, and more) to design PV systems in the past eight decades and hybrid systems as well. In another study, Kazem et al. [68] recommended linking the available software to MATLAB/Simulink and adding the social impact in addition to environmental evaluation to PV system design software. Also, to improve the flexibility for the end user by upgrading the optimization methods and software.

Farhana et al. [69] highlighted the potential of hybrid AI models in addressing grid stability problems within renewable energy sources, such as solar energy networks. In reviewing many articles, it is evident that hybrid AI is more efficient and surpasses traditional methods in predictive modelling and fault detection. Also, the review focuses on the progress made in real-time data processing and the adaptability of hybrid AI systems to complicated and geographically distributed networks, offering a solution for future smart grids, but the real-time data standardization continues. As the role of renewable energy grows, the use of hybrid AI models will play an essential role in advancing innovative grid technologies and supporting global sustainability goals [69].

Reliable grid management and the mitigation of operational risks depend on accurate solar output forecasting. To predict solar irradiance and photovoltaic (PV) power output, Jailani et al. [70] focused on long short-term memory (LSTM) models, which are especially useful in time-series forecasting. For forecasting, LSTM models outperform conventional machine learning models. Since the hybrid models must extract both spatial and temporal features, they typically perform more accurately than standalone LSTM models. Still, they also require more complex input data (such as images for CNN layers) and longer training times [70]. Batch size affects model performance; higher batch sizes result in lower accuracy.

The use of artificial neural networks (ANNs) for modelling solar energy (SE) devices is reviewed by Elsheikh et al. [71], with an emphasis on the benefits of ANNs over conventional theoretical and experimental approaches. ANNs save time and money by eliminating the need for intricate mathematical models and time-consuming experimental testing while providing high accuracy, generalization, and quick computation. Following its robustness and simplicity, the multilayer perceptron (MLP), with the Levenberg–Marquardt algorithm, is frequently utilized. The study recommends investigating other ANN types, such as ANFIS and recurrent neural networks. To improve performance by identifying the best network parameters, it also highlights the expanding trend of combining ANNs with metaheuristic optimization techniques such as genetic algorithm (GA), particle swarm optimization (PSO), grey wolf optimiser (GWO), and sine cosine algorithm (SCA). Furthermore, more sophisticated ANN variations, such as deep neural networks, extreme machine learning (EML), and ANFIS, are being developed.

## 5. General Overview of Fuzzy Logic

Fuzzy logic is a two-word concept consisting of "fuzzy" and "logic." The word "fuzzy" deals with uncertainty in a process or data, whereas "logic" is the study of correct reasoning. In this context, reasoning focuses on drawing conclusions based on available information [72]. Therefore, in combination with these phrases, fuzzy logic is defined as an artificial intelligence technique that has to do with the performance of reasoning, thereby facilitating the analysis and interpretation of imprecise data [73]. An advantage of fuzzy logic is the reduction in the complexity of modelling systems, which it offers because it needs fewer extensive mathematical formulations. Models associated with fuzzy rules are said to be easy to understand because of the employment of the IF-THEN rules and linguistic terms, and, hence, do not require learning algorithms. To compare fuzzy, vague, or ambiguous objects, Shimura [74] introduces a relativity notion. In this case, p and q are variables defined by the universe (U), and define two pairwise functions, $f$q(p) and $f$p(q), as the membership function of q with respect to p and p with respect to q, respectively. Considering the membership value measurement whereby $p$ is chosen over q, Equation (1) (relativity function) applies:

$$f(p|q) \ = \ fq\ (p)max\ [fq(p),\ fp\ (q)] \tag{1}$$

where $f(p|q)$ is the relative function, which represents the membership of $p$ to $q$. The C matrix (C for comparison) is used to rank different fuzzy sets. For instance, take the following:

$$Cj' \ = \ max\ f(pj|S),\ j \ = \ 1,\ 2\ldots,\ m. \tag{2}$$

or

$$Cj'' = min\ f(pj|S),\ j = 1,\ 2\ldots,\ m \tag{3}$$

where

$Cj'$ or $Cj''$ is the membership ranking value for the jth variable. The maximum and minimum functions are used to rank different options in terms of the benefit and cost of a solar energy system, respectively. However, in fuzzy logic, the membership function is an essential factor and plays a critical role, especially in facilitating the conversion between crisp and fuzzy data. The membership function of a fuzzy set A is denoted as $\mu_A$, and the membership value of $x$ in A is represented as $\mu_A(x)$. Importantly, the membership function is commonly triangular and trapezoidal in shape and is used and applied by researchers. The FL also helps in the design consideration, thereby characterizing the fuzzy set while developing a fuzzy logic system. A popular example of the membership function is the triangular membership function, which is used to explain and show the different speeds of a fuzzy set. Examples of fuzzy logic techniques include fuzzy inference systems (FIS), adaptive neuro-fuzzy inference systems (ANFIS), and fuzzy c-means techniques (FCM) [72]. Despite the application of fuzzy logic in well-established fields, its combination with more artificial intelligence, such as deep learning, genetic algorithms, etc., provides more problem-solving capability. The study by Das [75] mentioned that integrating deep learning and fuzzy logic helps facilitate the imprecision handling, thereby providing a scenario for complex learning capabilities.

With fuzzy logic, the criteria weight is measured and is of importance in the decision-making process. One fuzzy measure concept, as proposed by Grabisch [76], is stated as $X = \{x_{1,}\ x_{2,} \ldots x_{n,}\ \}$ and is a universe of discourse and is finite; P(X) is the power set of X. Therefore, a fuzzy measure on X is a set function $m$: $P(X) \to [0,1]$ to satisfy the following conditions:

1. $m(\varnothing) = 0, m(X) = 1$ (boundary conditions);
2. If $A, B \in P(X)$ and $A \subseteq B$ then $m(A) \leq m(B)$ (monotonicity).

From the above expression, it is evidently clear that the measurement of fuzzy employs the use of monotonicity instead of the additivity property. This shows that the weight criteria are independent and can be regarded as good modelling phenomena used for decision-making, as mentioned in Murofushi and Sugeno [77]; Liginlal and Ow [78]. The monotonicity of the fuzzy measure distinguishes it from other traditional and conventional weighting methods. Nevertheless, fuzzy logic combined with a genetic algorithm provides an enhanced optimization capability, such as effectiveness in engineering applications [79].

To address the intermittency of electricity from renewable energy and its unreliability, and to educate energy users on the necessity of using clean energy sources, a realistic and reliable model needs to be developed. Fuzzy logic is an example of such a model. The model is important in ensuring fair budget reallocation and spending towards enhancing the use of renewable energy. According to Suganthi et al. [24], the fuzzy logic model can be employed to plan energy, thereby arriving at pragmatic solutions effectively. This also conceptualized the system fuzziness into a crisp, quantifiable parameter, as mentioned in the Suganthi et al. [24] study. It is interesting to state that, in relation to energy systems, fuzzy logic is classified broadly as fuzzy models, hybrid models, and multi-criterion decision models, as presented in Figure 1.

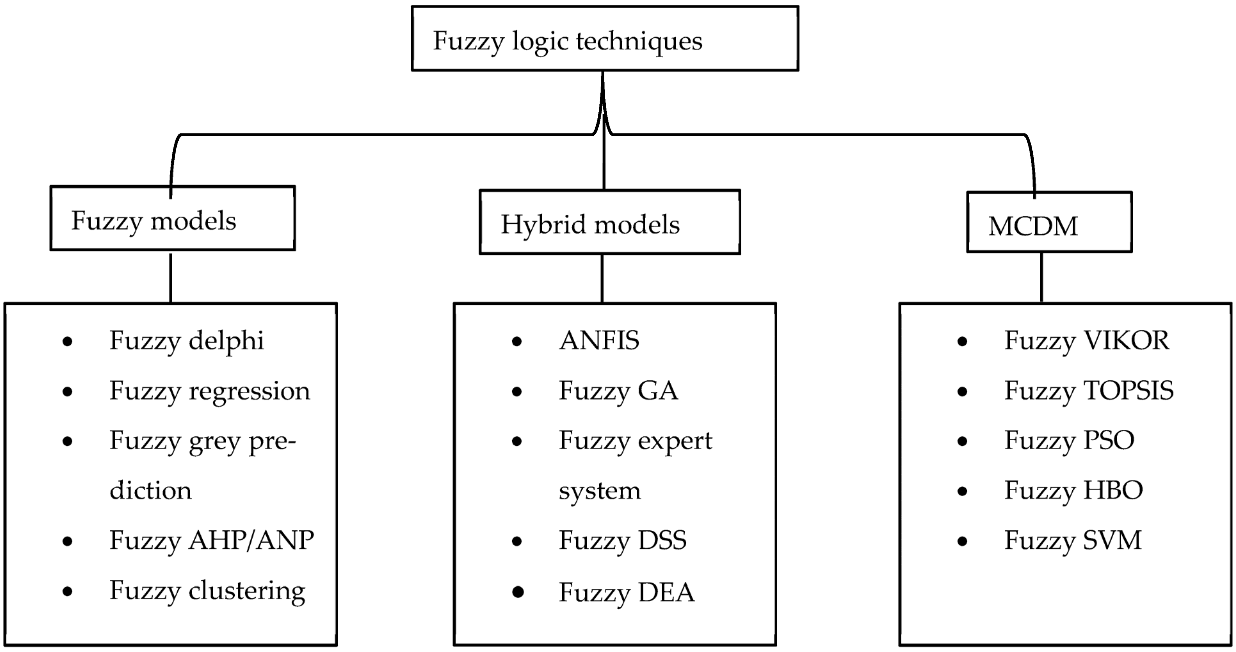


**Figure 1.** Classification of fuzzy logic techniques for solar energy applications.

To illustrate Figure 1 further, Tables 2–4 briefly describe the application of these classifications of fuzzy logic techniques in relation to solar energy systems. The fuzzy model, as illustrated in Table 2, is classified as ‘simple’ based on its complexity features, which is an advantage for mainly predicting or grading solar energy systems. For the hybrid models in Table 3, the essential ones are classified as ‘medium’ in complexity. Potentially applicable for the accurate simulation of the performance of solar energy systems. The model is said to progress based on the justification of the accuracy relating to cost and complexity. Similar to other models, the MCDM is categorized as ‘complex’. This is because experts are required to run and operate the packages as well as interpret the results. An area of application regarding the importance of the MCDM deals with testing the numerical and simulation analysis of renewable energy systems [24].

**Table 2.** Classification of fuzzy models in relation to solar energy systems.

| Fuzzy Delphi | Fuzzy Regression | Fuzzy Grey Prediction | Fuzzy AHP and ANP | Fuzzy Clustering | Fuzzy Approach |
|---|---|---|---|---|---|
| Used when the expert's response is of a fuzzy nature. Also used for the prediction purposes of solar energy performance.<br>The Fuzzy Delphi steps are collections of opinions of a decision group; set up triangular fuzzy numbers; defuzzification; and screen evaluation indexes [80].<br>Under set up triangular fuzzy numbers the fuzzy weight $\widetilde{w}_j = \left(a_j, b_j, c_j\right)$ where $a_j = \underset{i}{min}\left\{a_{ij}\right\}$; $b_j = \frac{1}{n}\sum_{i=1}^{n} b_{ij}$; $c_j = \underset{i}{max}\left\{c_{ij}\right\}$ for $i = 1, 2, \ldots, n, j = 1, 2, \ldots, m$.<br>Under defuzzification the fuzzy weight is defuzzified and the formula, $S_j = \frac{a_j+b_j+c_j}{3}$ for $j = 1, 2, \ldots, m$. These Fuzzy Delphi methods are used in lubricant regenerative technology selection. | The variables (independent and dependent) in terms of data are captured in a fuzzy manner. Hence, the derived regression equation is used to determine the effect of the variables.<br>The Fuzzy regression analysis can be shown as the formula, $Y = A_0X_0 + A_1X_1 + A_2X_2 + \cdots + A_iX_i + \cdots + A_pX_p$ when $A_i$ is set as triangle fuzzy numbers for $i = 0, 1, 2, \ldots, p$ and $X_0 = 1,\ X_i > 0,\ i = 1, 2, \ldots, p$ are all variables with crisp values while assuming fuzzy parameter $A_i = (c_i, a_i, b_i),\ i = 1, 2, \ldots, p$.<br>Then, according to triangular fuzzy numbers of calculations, the fuzzy number $Y = \left(\sum_{i=0}^{p} c_i x_i,\ \sum_{i=0}^{p} a_i x_i,\ \sum_{i=0}^{p} b_i x_i\right)$.<br>The Fuzzy regression can be applied on air cargo volume forecast [81]. | The grey area is captured by the fuzziness in the variables which is considered for the dependency prediction. Also used for prediction purposes. GM(1,1) is the most commonly used grey prediction [82], described as $x^{(1)} = IAGO.GM(1,1).AGO.x^{(0)}$ where $x^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(k)\right)$ is a non-negative original data sequence for $k \geq 4$. $x^{(1)}$ is a prediction value of $x^{(0)}$, AGO takes the accumulated generating operation on $x^{(0)}$, and IAGO takes the inverse accumulated generating operation on $x^{(1)}$. Hence $x^{(1)}(k+p) = x^{(0)}(1) - ba1 - e^{a}e^{-a(k+p-1)}$ where $p$ is the forecasting step, $a$ and $b$ are the development coefficient and the grey input, respectively [83]. Y.F Wang [84] used the formula $x^{(1)}(k+p) = x^{(0)}(1) - ba1 - e^{a}e^{-a(k+p-1)}$ to predict solar energy price. | Employed to determine or finding the relative importance of the variables and energy resources (in terms of energy systems). To calculate the value of Fuzzy Synthesis the formula $\sum_{j=1}^{m} M^{j}{}_{gi} \times \left[\sum_{i=1}^{n}\sum_{j=1}^{m} M^{j}{}_{gi}\right]$ where $M$ is the triangular fuzzy number, $m$ is the number of criteria, $i$ is the rows, $j$ columns and $g$ is parameter $(l, m, u)$. The formula above is used in decision support system for solar PV recommendation [85]. | Fuzzy clustering is applicable for grouping of solar energy resources based on cost, availability, etc. Also help to demarcate the clusters and draw boundaries. In Fuzzy clustering the formula $J_m = \sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^{m}\left\Vert x_i - c_j\right\Vert^2$, $1 \leq m < \infty$ where m is any real number greater than 1, $u_{ij}$ is the degree of membership of $x_i$ in the cluster $j$. $x_i$ is the $d$-dimensional measured data, $c_j$ is the $d$-dimensional centre of the cluster, and $\Vert * \Vert$ is any norm expressing the similarity between any measured data and the centre. [86]. This formula is applied in developing a fuzzy clustering model for better solar energy use as regards management systems. | Essentially used to accurately capture fuzziness while ranking the variables.<br>One of the steps for the Fuzzy approach is defuzzification. There are many methods used for defuzzification; one of the most popular methods is the Centre of Gravity (COG) method. According to the COG, the output crisp value is calculated using the formula $y_{crisp} \frac{\sum_i c_i \int m_{yi}(x)dx}{\sum_i \int m_{yi}(x)dx}$ where $c_i$ is the centre of the membership function, the integral $\int m_{yi}(x)dx$ represent the area under the membership function $m_{yi}(x)$ corresponding to the attribute of the output linguistic variable $y$ [87]. The formula stated above is used for solar energy estimation. |

**Table 3.** Classification of the hybrid model in relation to solar energy.

| ANFIS | Fuzzy GA | Fuzzy Expert System | Fuzzy DSS | Fuzzy DEA |
|---|---|---|---|---|
| Employed in solar PV control and smart grid systems. There are two rules under ANFIS, Rule 1: If ($v$ is $V_1$) and ($d$ is $D_1$) then $f_1 = p_1 v + q_1 d + r_1$; Rule 2: If ($v$ is $V_2$) and ($d$ is $D_2$) then $f_2 = p_1 v + q_2 d + r_2$ where $p_1, p_2, q_1, q_2,\ r_1$ and $r_2$ are linear parameters and $V_1,\ V_2,\ D_1$ and $D_2$ are non-linear parameters, in which $V_1$ and $D_1$ are the membership functions of ANFIS. The layer-by-layer ANFIS formulae are. Layer 1: $O_{1,i} = \mu_{v,i}(v)$ for $i = 1,2$; $O_{1,j} = \mu_{d,j}(v)$ for $j = 1,2$ where $O_{1,i}$ and $O_{1,j}$ represent the output function and $\mu_{v,i}$ and $\mu_{d,j}$ denote membership function Layer 2: $O_{2,i} = w_i = \mu_{v,i}(v).\mu_{Dj}(d)$ for $i = 1,2$ Layer 3: $O_{3,i} = \overline{w_i} = \frac{w_i}{w_1+w_2}$ for $i = 1,2$ Layer 4: $O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i v + q_i d + r_i)$ for $i = 1,2$ Layer 5: $O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{w_1+w_2}$ for $i = 1,2$ [88]. These formulae can be used for modelling and simulation of an ANFIS. | Used in control solar PV for finding the best solar energy generation terrain. One of the formulae used under Optimized Fuzzy Genetic Algorithm (OFGA), it denotes the population selection where for every population $y = (y_1, y_2, y_3, \ldots, y_n)$, it defines the rules to separate the data into various clusters $C = (c_1, c_2, c_3, \ldots, c_m)$ to minimize the data feature. The partition matrix $W = w_{ij}$ which indicates that element $y_i$ belongs to $C_j$: $\text{arg\_}\underset{C}{min} = \sum_{i=1}^{i=n} \sum_{j=1}^{j=m} w_{ij} \left\| y_i - c_j \right\|$ [89]. This formula is used to enhance a multimodal biometric recognition approach for smart cities based on an optimized fuzzy genetic algorithm. | These are AI systems used to identify the best solar energy resource thereby maximizing its available resources. A formula which is used under the Fuzzy Expert System for Solar PV Plant is the formula for calculating the Pearson's coefficient of correlation $r$ between $x$ and $y$, and the formula is as follows: $r = \frac{\sum(x_i-\overline{x})(y_i-\overline{y})}{(n-1)\sigma_x\sigma_y}$ where $\overline{x}$ and $\overline{y}$ are the respective means of $x$ and $y$, $n$ is the population size. $\sigma_x = \sqrt{\frac{\sum(x_i-\overline{x})^2}{(n-1)}}$ is the standard deviation of $x$; $\sigma_y = \sqrt{\frac{\sum(y_i-\overline{y})^2}{(n-1)}}$ is the standard deviation of $y$ [90]. The formula above is used for a Fuzzy Expert System for determining state of solar PV power plant based on real-time data. | Helps to identify the decision model given in a solar energy situation The formula that is used to optimize the path planning of industrial robots is optimized by fuzzy reasoning mechanism. The variables are defined by fuzzy sets $A = \{A_1, A_2, A_3\}$ each representing different fuzzy state (near, middle, long, respectively). Each fuzzy set has its membership function, for example: $\mu_A(x) = \frac{1}{1+(x-c)^2}$ where $c$ is the membership centre and $x$ is the value of the input variable. The formula for calculating fuzzy reasoning is $\mu_{output}(z) = \min\left(\mu_{input1}(x), \mu_{input2}(y)\right)$ where $\mu_{input1}(x), \mu_{input2}(y)$ respectively for the membership of the input variable $\mu_{output}(z)$ as output variable of membership degree. These formulas are used for the design and implementation of industrial robot path planning based on fuzzy decision support systems [91]. | Help in determining the best combination of solar energy resources used in various situations/regions Fuzzy DEA slacks-based model uses the formula: Assuming that there are $j = \{1, 2, \ldots, N\}$ decision-making units (DMUs), each with $M$ fuzzy inputs $\widetilde{X}_j = \left(\widetilde{x}_{1j}, \ldots, \widetilde{x}_{Mj}\right) \in (TrFN)_+^M$, and $S$ fuzzy outputs $\widetilde{Y}_j = \left(\widetilde{y}_{1j}, \ldots, \widetilde{y}_{Sj}\right) \in (TrFN)_+^S$ then, $T_{FDEA} = \{\left(\widetilde{x}, \widetilde{y}\right) \in (TrFN)_+^{M+S} : \widetilde{x}\sum_{j=1}^N \lambda_j \widetilde{x}_{ij} \forall i,\ \widetilde{y}\sum_{j=1}^N \lambda_j \widetilde{x}_{rj} \forall r, \sum_{j=1}^N \lambda_j = 1,\ \lambda \in \mathbb{R}_+^N\}$, where FDEA stands for Fuzzy DEA. Calculating the slacks-based measure of inefficiency $\widetilde{I}\left(\widetilde{X}_p, \widetilde{Y}_p\right) = Max \sum_{i=1}^M \widetilde{\beta}_i + \sum_{r=1}^S \widetilde{y}_r$ [92]. This formula is used for a fuzzy DEA slacks-based approach. |

**Table 4.** Classification of the MCDM in relation to solar energy.

| Fuzzy VIKOR and TOPSIS | Fuzzy SVM/PSO/HBO |
|---|---|
| Basically, they are used for the optimization of solar energy systems. Applicable in the solar energy sector for control systems.<br>Fuzzy TOPSIS is used to solve the Multi-Criteria Decision Analysis (MCDA) problems of uncertainty, vagueness, and crisp data that are insufficient to simulate real-world situations [93]. Assuming a panel of $k$ experts $(D_1, D_2, \ldots, D_k)$ evaluated $m$ pathways $(P_1, P_2, \ldots, P_m)$ with respect to $n$ criteria $(C_1, C_2, \ldots, C_n)$, the fuzzy decision matrix is given by the following: $D = \begin{array}{c} \\ P_1 \\ P_2 \\ \vdots \\ P_m \end{array} \begin{array}{c} \begin{array}{cccc} .C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix} \end{array}$. The $D$ matrix is normalized by using the linear scale, and the following is obtained:<br>$D = \left[r_{ij}\right]_{m \times n}$ where $r_{ij} = \frac{x_{ij}}{max x_{ij}}$. The formula stated above is used for an integrated fuzzy decision support system for analyzing challenges and pathways to promote green and climate-smart mining [94]. | These are machine learning tools used to unpack the mystery behind solar energy data as well as for the accurate prediction of outcomes. Applicable in the solar energy sector for control systems. The Fuzzy SVM optimization function can be written as follows: $min: \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n} s_i \varepsilon_i$ such that $y_i(w * \phi(x_i) + b) \geq 1 - \varepsilon_i$ for $\varepsilon_i \geq 0$ where $w^2$ represents the margin ratio of the generalization ability of the learning model, $s_i$ represents the fuzzy membership value corresponding to different samples, $\varepsilon_i$ is the acceptable training error degree of the corresponding instance $x_i$, and $C > 0$ is called the penalty parameter. The formula above is used for deep learning-based imbalanced classification with fuzzy SVM [95]. |

The contribution of fuzzy logic models to the decision-making process of solar energy systems lies in making it possible to illustrate risk factors and introducing the concepts of linguistic variables of data from solar energy applications. In solar energy industries, fuzzy sets allow the formalization of the relationship between the factors of risks and the real interactions studied in the electricity power industries. Furthermore, in connecting solar energy to the power supply system, decision-making is required. This is possible through the fuzzy methods under incomplete information conditions, thereby synthesizing and analyzing qualitative values [96]. As mentioned in Zenani et al. [30] and Stepanenko et al. [96], the mechanism of fuzzy logical inference involves four stages. These are the fuzzification method, the base of rule, the aggregation method, and the defuzzification method, as shown in Figure 2.

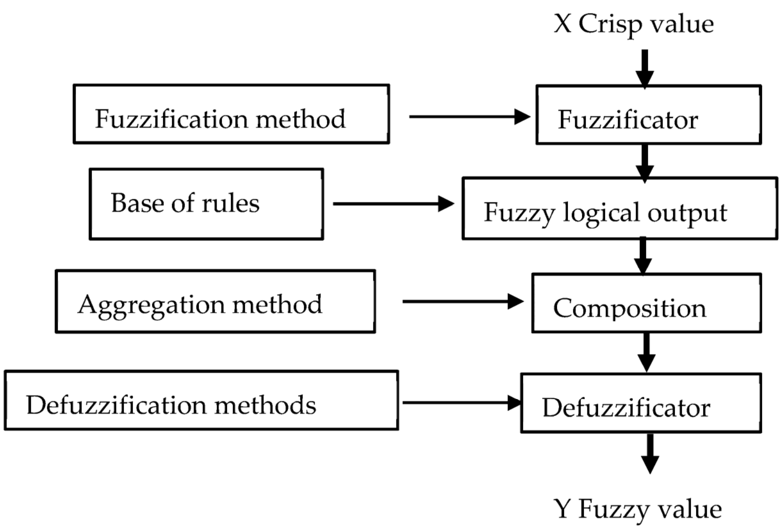


**Figure 2.** Schematic diagram of a fuzzy logic model system.

## 6. Studies on the Application of Fuzzy Logic in Solar Energy Systems

One of the benefits of fuzzy logic deals with decision-making. This was seen in the study on comparing different solar systems for various applications conducted by Mamlook et al. [97]. The authors employed fuzzy logic to determine the order of priority of solar systems in Jordan based on costs and benefits. For comparison's sake, the various solar system applications studied include solar water pumping (SWP), solar distillation (STILL), solar water heating (SWH), solar photovoltaic (PV), solar pond (POND), and solar space heating (SSH). With the application of fuzzy set data, used for the comparison analysis, in terms of the benefit, STILL has the highest priority because of its highest overall fuzzy relative weight of 2.29, followed by POND (1.62), SWP (1.39), and SSH of 1.06. On the other hand, as regards cost, SWH is the least attractive because of its highest fuzzy relative weight of 1.78, followed by PV (0.71), SWP (0.61), and SSH (0.49). STILL (0.41) and POND (0.46) are the most attractive, respectively, based on their lowest relative weight. Therefore, from the benefit-to-cost ratio, the STILL (5.58 relative weight) was reported to be the best choice and preferred. Hence, it was regarded as the highest priority.

Preliminary results were obtained in a study by Charabi and Gasti [98] on assessing solar energy resources in Oman. With the application of the GIS-based spatial fuzzy multi-criteria evaluation approach, the land suitability for implementing PV farms was assessed. The assessment approach was based on the FLOWA module, which applies fuzzy quantifiers within the ArcGIS environment. This plays a vital role by incorporating the uncertainty of expert opinion in relation to their criteria and weight, as well as providing a mechanism to guide decision-making using a combination of multi-criteria procedures. To determine the relative importance of land suitability with respect to PV farms, according to the pairwise comparison for objectives (solar radiation, constant layer, and distance to major roads), these were calculated against each other (solar radiation, constant layer, and distance to major roads). The reported weights include solar radiation at 0.545, constant layer at 0.287, and distance to major road at 0.168. This implies that solar radiation (0.287) is a relative intensity importance factor affecting the location of large PV farms in Oman, while the distance to major roads is the least (0.168). However, the development of the first geographical mapping model to locate the most suitable and appropriate site for different PV technologies in Oman was considered in the study. Based on the resultant maps of the analysis, 0.5% of the land area was said to be highly suitable for the implementation of the PV farm. However, with reference to the different PV technologies considered in the study, the CPV technology provided the features required for the implementation of the large solar plants, thereby generating 45.5 times the present total power demand in the country.

Over the years, the site selection for solar thermal power plants (STPPs) has faced some challenges, such as the independence of the assumption of the MCDM method used and the lack of quality information for evaluating the site. These challenges increase the possibility of decision-making mistakes and decrease evaluation quality. To address this problem, Wu et al. [99] proposed a decision framework to evaluate and select the best site for a solar thermal power plant (STPP). The study is critical because it examines the role and contribution of site selection when considering the life cycle of a solar thermal power plant. Therefore, the fuzzy logic method's multi-criteria decision-making (MCDM) tends to be vital in the selection process of STPP. Based on this, the authors employed a linguistic Choquet integral (LCI) with a decision-making method to rank the alternative sites. The fuzzy measure was adopted to solve the critical expert's dependence problem. In the study, Wu et al. [99] identified the criteria and sub-criteria for selecting the STPP site, thereby providing a practical framework to evaluate the selected site. The study mentioned energy, infrastructure, land, and environmental and social factors as the criteria used. From the theoretical modelling and empirical results, these challenges were handled through the decision framework, resulting in an outstanding result.

The complexity of energy management in a commercial building seems to be a problem because of various factors such as the production of PV, electricity price variation, kinds of consumption, and the agreement of purchase. To address this problem, Zhang et al. [100] modelled a commercial building integrated with PV and storage systems and proposed a methodology for designing an energy-management strategy. This is necessary to achieve the aim of the study, which deals with reducing the cost of energy bills and emissions due to $CO_2$. Therefore, the methodology developed in the study was based on a graphical approach and a fuzzy logic supervision strategy. The proposed fuzzy logic supervision strategy should be able to satisfy the economic and ecological objectives of the controlled system on which the simulation results are based. In the study, the economic criteria are based on the annual premium (€) and the electricity cost of consumption (kWh), whereas the ecological criteria are the emission of $CO_2$. From the simulation results, two cases were used: Case A (configuration without storage and PV system) and Case B (configuration with storage and PV system). These results were formulated under the annual premium, consumption for one week, and $CO_2$ emission. It was reported that case A has an annual premium of EUR 79,344, consumption for 1 week of EUR 8782, and $CO_2$ emission of 11.604 T. On the other hand, case B has EUR 54,747 €, EUR 6066, and 8.541 T for annual premium, electricity consumption, and emission of $CO_{2,}$ respectively. Considering the differences in annual premium, consumption for one week, and $CO_2$ emission for cases A and B, the following were reported: EUR −24.597 (−31.00%), −2716 € (−30.93%), and −3.063 T (−26.40%), respectively. This implies that the annual premium and electricity consumption can be reduced by 31% for one year and 30.93% for one week, respectively, whereas the $CO_2$ emission can be reduced by 26.40% for the same one week. Therefore, the reduction, as seen in the result, is based on the proposed fuzzy logic supervision strategy used in the study. Hence, this is based on the attributes of the evaluation carried out by some economic and ecological indicators.

To determine the role of consumer acceptance and the model effect on residential PV adoption, a survey was conducted to understand the perceptions of the technology. These variables' perceptions include perceived cost, perceived maintenance requirement, and environmental concern. According to the customer maintenance survey, they are regarded as the top three variables that affect customers' decision-making process to purchase solar panels. To this effect, Zhai and Williams [101] conducted a study to evaluate the purchasing probability of a residential PV system using fuzzy logic. Also, the study focuses on building a fuzzy logic model to relate the perception variable of the consumers, known as the model input, with the purchasing probability, referred to as the model output. From the statistical result, the peak of the purchasing probability distribution of adopters, non-adopters, and the mean value of the probability are 100%, 20%, and 30%, respectively. Based on the fuzzy logic model, the purchasing probability distribution for adopters approaches 1.0, which is an indication that a purchase has already been made by the adopters. It is interesting to point out that the output of the fuzzy logic model is the adopter and non-adopter. In addressing the social issue of PV technology and dealing with imprecision and insufficient information, the fuzzy logic inference model has the potential to provide an alternative solution. Despite the study's success, the authors lamented data limitations (a relatively small sample of adopters) as a significant barrier to the study. Therefore, further study recommends a larger data sample for the validation of the model.

The exploration of the primary resistance and key factors that affect the application of renewable energy technologies in Taiwan buildings was conducted by Liu et al. [102]. Taiwan is regarded as highly vulnerable in terms of energy security; however, its geographic condition and features for solar energy development have resulted in a considerable advantage. Based on the evaluation decision-making system model and expert decision-making groups, the study employed the fuzzy set methodology through the Fuzzy Delphi Method (FDM) to assess the application of solar energy systems. Also, the conversion of fuzzy ranges to crisp variables helps to accurately sieve through the decision-making process in the minds of consumers. Figure 3 shows the application steps, operational process, and framework of the FDM. However, due to the lack of ambiguity of the traditional Delphi method, the FDM is combined with fuzzy theory to address the challenge. To avoid the impact of extreme values, as mentioned in Ishikawa et al. [103], the opinions of expert decision-making groups are integrated into fuzzy numbers, thereby utilizing the geometric mean for the basis of decision-making and screening assessment by the specialist decision-making group. Therefore, findings from the study stated that the main influences and key factors, as well as the proposed energy development strategies, are required to improve the quality and quantity of the application of renewable energy and national energy competitiveness.

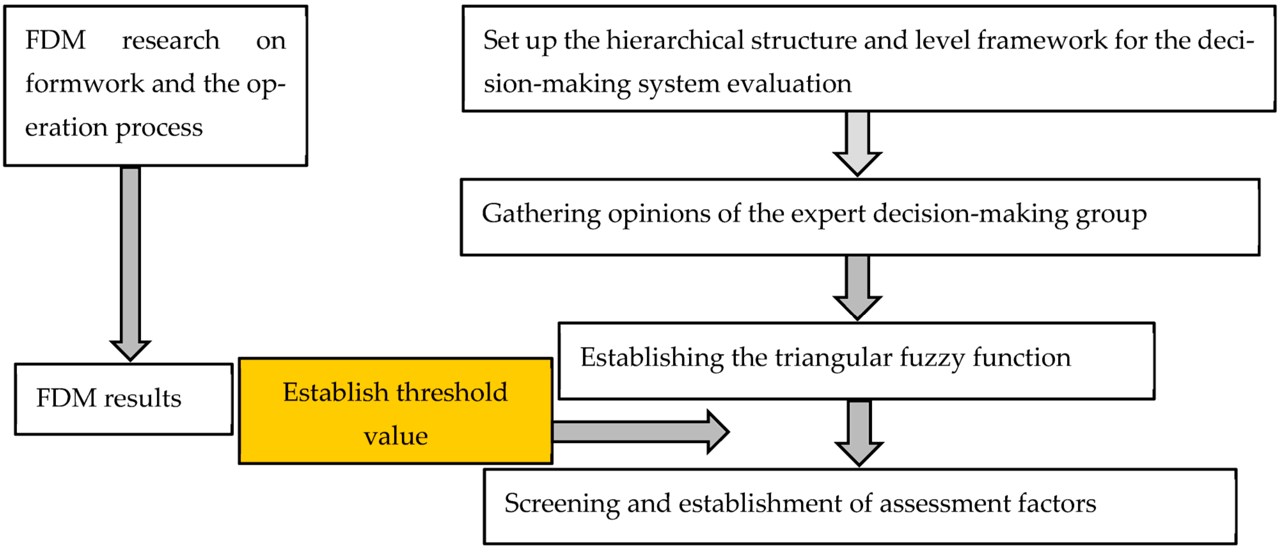


**Figure 3.** The Process of the Fuzzy Delphi Method.

Due to the easy implementation of the perturbation and observation (P&O), maximum power point tracking (MPPT) algorithms are widely employed in PV systems. To this effect, a comparative study was conducted on the potential and actual performance of four P&O MPPT algorithms. In the study, as well, the performances of three variable-size P&O MPPT algorithms were discussed. These included the peak current controlled scheme, the based plane region, and the non-switching circuit zones. In the study, the features of the four peak current controls based on the P&O MPPT scheme included scheme III.A (standard), scheme III.B, scheme III.C, and scheme III.D. These were employed for the simulation result dealing with the rise time from start up to peak power and power drop (steady state). It was observed that 0.32 ms, 0.27 ms, 0.17 ms, and 0.17 ms were reported for scheme III.A (standard), B, C, and D, respectively, for the rise time from start up to peak power, while the power drop (steady state) has scheme III. A, B, C, and D of high, lowest, lowest than standard scheme, and lowest, respectively. This finding revealed that the fuzzy scheme presents a faster transient response and high-power yield in the steady state when compared to the standard P&O MPPT algorithm. In the study, D'Souza et al. [104] also looked at the use of fuzzy logic integrated with a non-switching zones scheme to implement variable size perturbation. This is necessary for the improved transient and steady-state responses. Based on this, the study mentioned that the non-switching zones with a reduced fuzzy controller in the MPP region have the best performance. The assumption for this performance is based on the absence of the processing speed of the digital signal processor (DSP) and the computation burden of the algorithms. With reference to D'Souza et al. [105], the reduced fuzzy and non-switching zones are often used to improve the performance of the previous scheme under steady-state conditions. It was reported that three of the P&O MPPTs use variable-size perturbation to improve the transient and steady-state performances, whereas the fourth one deals with fixed-size perturbation. The study was simulated in a MATLAB/Simulink environment to verify the potential performance of the four schemes. With the reduced fuzzy P&O MPPT algorithm, an improved outcome was yielded. Hence, these are used to reduce oscillations and increase steady-state power yield.

Niapour et al. [106] propose a single-stage Z-source inverter (ZSI) for the extraction of the maximum power of the PV array as well as for the supply of the brushless DC (BLDC) using a fuzzy logic incremental conductance (FL-IC) MPPT scheme. The FL-IC was implemented for the precise performance of the maximum power point tracking of the PV array. The study was motivated to reveal that a considerable amount of energy can be saved in the PV water-pumping systems by replacing conventional DC with BLDC motor, thereby utilizing ZSI as opposed to the use of a traditional double-stage converter. The water-pumping system comprised a brushless DC (BLDC) motor with a centrifugal pump supported by a ZSI. According to the author, the ZSI was fed by a PV array that needs to be improved. Although there has been a conventional method of double-stage converters, the proposed FL-IC MPPT provides some modifications. The authors employed the PSCAD/EMTDC linked to MATLAB software to simulate the different PV array operation conditions in the study. In terms of validation, the simulation result was compared with previous work under the same operational conditions. The authors highlighted that the study could simulate water-pumping systems to widely accommodate worldwide, thereby utilizing solar power as a clean energy source and improving efficiencies.

A novel multi-model neuro-fuzzy-based MPPT for a three-phase grid-connected PV system was conducted by Chaouachi et al. [107]. With the proposed model, the reference PV voltage that guarantees optimal power transfer is said to be predicted. This occurred between the PV generator and the primary utility grid. Comparing the neuro-fuzzy network model and the conventional single neural network, the study states that the former has the advantage of distinct generalization ability based on the non-linear and dynamic behaviour of a PV generator. Furthermore, the application of a neuro-fuzzy network in the study offers a set of local models that emulate the behaviour of PV generators in terms of complexity and nonlinearity within a wide range of operating conditions. However, for the simulation process, the study considered evaluating the estimation error of the performance of the neuro-fuzzy network and a single ANN. Hence, estimation error refers to the statistical approach to the differences between the experimental and the estimated values. Therefore, the study reported 0.139 and 2.496 as the mean absolute error (MEA) for the neuro-fuzzy and single ANN estimators, respectively. Conversely, based on the power efficiency, the neuro-fuzzy method was said to have achieved 6.85% power efficiency when compared with the single ANN. Also, it was said to have a 2.73% comparison to the experimental dispositive based on the P&O algorithm. This shows that the neuro-fuzzy MPPT methodology has a better performance than the single ANN.

In a similar study, Sarah and Ouali carried out a comparison of fuzzy logic and neural networks in MPPT for PV systems [108]. In this case, the solar radiation and PV cell temperature, the two MPPT parameters, were used as the input, while the maximum power was the output. It is interesting to point out that both fuzzy logic and neural networks can model dynamic complex systems with respect to time, following non-linear laws. The fuzzy logic and neural network employed the DC-DC inverter to arrive at the MPPT, from which the data for climatic conditions for the solar radiation and PV cell temperature were obtained. For the optimum duty cycle error and maximum power error, the fuzzy logic reported 2.70 and 0.07, compared to the neural network with 17.15 and 0.53, respectively. This indicates that fuzzy logic is the best method among the neural networks because the former gives the minimum total error compared to the neural method. Therefore, the experimental result of the MPPT controller via fuzzy logic has higher power efficiency than the neural network. Hence, there is a need to integrate or combine fuzzy logic and neural networks for efficient system performance.

In handling complexity, uncertainty, and non-linearity, Azadeh et al. [109] presented an approach based on the flexible neuro-fuzzy for location optimization of solar plants. The flexible approach includes ANN and fuzzy data environmental analysis (FDEA). The use of FDEA and ANN in the study was based on a normality test. Hence, these methods were essential to determine the ranking and assess the potential location for installing solar plants. The data environmental analysis (DEA) and FDEA are employed for the ranking of 150 solar power units (SPU). The input variables include the cost of land and the intensity of natural disaster occurrence, while the output variable includes population, human labour, solar global radiation, and distance of power distribution, as well as availability of water and proper topographical areas. With the fuzzy logic technique employed in the study, the DEA was used for the ranking of the SPUs as well as validation and verification of the obtained results of FDEA at $\alpha = 1$ using the Spearman correlation test. The Spearman non-parametric test was useful for testing the correlation of the ranking data. The $\alpha$ values used in the study were at 0.1, 0.3, 0.5, 0.7, 0.9, and 1 with their corresponding Spearman correlation index of 0.46, 0.45, 0.48, 0.63, 0.78, and 0.87, respectively, for DEA and FDEA values. Having the highest Spearman correlation index of 0.87 for $\alpha = 1$ means that the ranking results by both DEA and FDEA are verified and have a relatively high degree of confidence. On the other hand, for the normality test, the Kolmogorov–Smirnov Test was used. The data generated was the same for $\alpha$ values as seen previously using the Spearman correlation with their corresponding $p$-values at 0.029, 0.080, 0.020, 0.007, 0.000, and 0.000. The result indicates that the FDEA at $\alpha = 0.3$ is the preferred model because of its higher $p$-value of 0.080 for ranking of SPUs. A previous study conducted by Azadeh et al. [110] used the data environmental analysis (DEA) as an optimization tool for the efficient location of solar plants. In the study, certain limitations were observed using DEA, which include easy detection of noise or error from data, thereby resulting in vibration caused in the obtained solution. Another limitation deals with the inaccurately measured and imprecisely defined data associated with evaluating solar plant units (SPUs). Therefore, to address and overcome these limitations, FDEA was employed while the ANN was used to deal with the data corruption based on complexity and non-linearity. Employing the Spearman correlation test reveals that the best model was reported at FDEA $\alpha = 0.3$ for the location optimization of solar units in Iran. The proposed model can handle uncertainty and noise in the dataset, according to Azadeh et al. [109], and is recommended for optimization problems of different solar locations.

A conceptual model using fuzzy analytical network process (FANP) with interpretive structural modelling (ISM), as well as benefits, opportunities, costs, and risks (BOCR), was developed in a study conducted by Lee et al. [111]. The essence was to facilitate the prosperity of the PV silicone solar cell power and have the potential to handle complicated product-strategy problems, thereby leading to an outstanding result. In addition, the FANP + ISM + BOCR helps to analyze the correct strategic process of a large firm in a PV silicone solar-cell power network. As seen in Figure 4, the FANP + ISM + BOCR consists of five steps. A successful implementation of these steps is an instrument for receiving support from central authorities at the industrial level, for instance, in Taiwan, where the study was conducted. Also, the model can be utilized to design a development plan. From the findings of the study, the proposed strategic products are being supported by the central authorities, as they match the future of solar PV. As a methodology in relation to the developed model, it is recommended that multiple-goal programming be combined into the developed model; this will reduce the resources of time and cost.

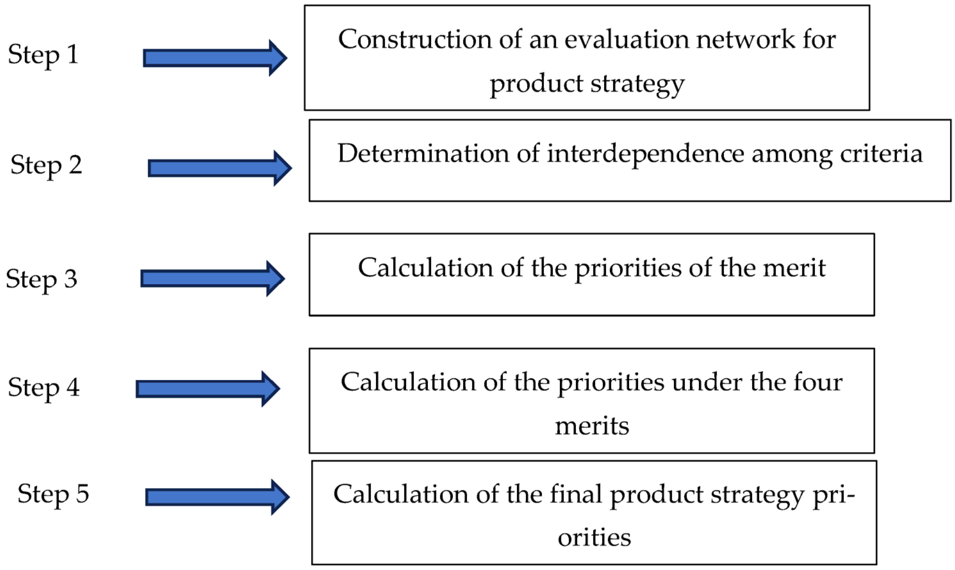


**Figure 4.** Flowchart of the FANP + ISM + BOCR.

To evaluate the viability of developing a solar PV project owned by large investor utilities in Florida was the aim of the study conducted by Zeng et al. [112]. Considering various factors such as the trade-off between the cost of generating electricity and the risk of investor-owned utilities, the authors developed a multi-objective decision model to determine the proportion of different sources of energy generation, thereby assisting in the decision-making process. This is necessary as it will help to reduce the risk of financial health and survival of investors, as well as lowering the cost of energy generation. Therefore, to calculate the total risk priority number (RPN) for each energy source, the failure mode and effect analysis was employed. The results revealed that solar PV has the lowest risk priority of 956 when compared to other energy sources considered in the study, such as coal and natural gas, with risk priorities of 1901 and 1873, respectively. From the study, it was deduced that the RPN for an investor-owned utility is determined based on the type of failure and failure mode number in the study area (Florida). Due to the uncertainties of the levelized cost of electricity (LCOE) and the risk level of the failure modes, the authors also used the fuzzy methods, incorporated with an equivalent crisp model. This is derived and solved by an optimization algorithm for multi-objective particle swarm optimization (PSO). To determine the most cost-effective solutions, the monetary value needs to be assigned to the risk. This was the case in the study, thereby showing that Florida Power and Light reduced RPN by 21 in 2016. The results increase the cost per kWh by USD 0.004 kWh. Thus, the authors opined that transferring the risk-priority number into a cost per kWh value is a possible way to select the most cost-effective solution. However, the PSO is regarded as an optimization technique dealing with swarm intelligence. Hence, its involvement in the study solves problems such as non-linear, discontinuous, and non-convex objective functions as well as constraints. Notably, the LCOE is mentioned in the study because it is most frequently used when comparing the generation of electricity technologies and discussing grid parties for emerging technologies [113]. For the decision makers, the multi-objective model helps determine the proposition of different generations of energy, thereby reducing risk related to financial health and survival of investor-owned utilities. The study's findings were used to evaluate the investor-owned solar PV projects in Florida.

Having looked at the previous studies of fuzzy logic application to solar energy systems, Table 5 presents a comparison summary detailing the type of application and a brief discussion from various studies.

Evidently, decision-making selection has been seen as one of the objectives of fuzzy logic techniques. Based on this, Figure 5 presents the schematic flow diagram of the procedure required for the decision-making selection specifically for renewable energy systems. One factor to consider in the decision-making process deals with the determination of weight criteria (Refer to Figure 5).

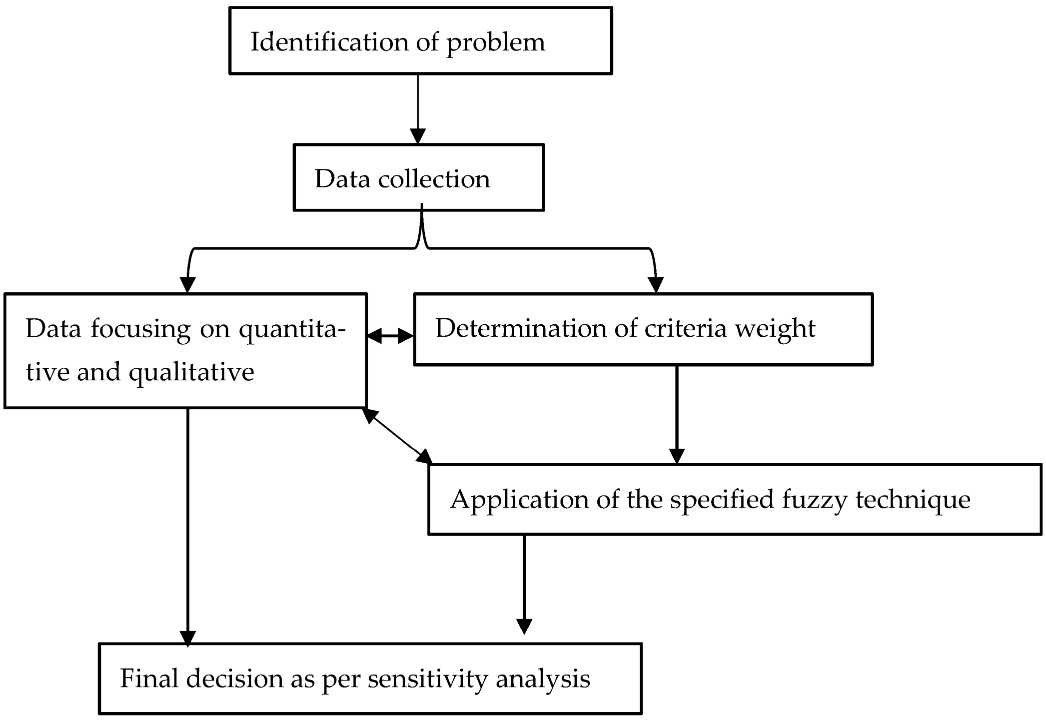


**Figure 5.** Flow diagram illustrating the decision-making selection procedure of solar energy systems {Extracted from Taylan et al. [125]}.

To conclude this section, it is necessary to briefly summarize the advantages and limitations of the fuzzy logic techniques in relation to solar energy processes. This is presented in Table 6.

**Table 5.** Summary comparison of fuzzy logic techniques with their respective application type and findings in relation to solar energy systems, including advantages and disadvantages.

| Fuzzy Logic Technique | Type of Application | Brief Discussion | Advantages of FLT | Disadvantages of FLT | References |
|---|---|---|---|---|---|
| FAHP and FANP | PV silicone solar cell and solar power plant | The techniques are used to organize complex things into a well-structured hierarchical order. Furthermore, it handled a complicated strategic problem, thereby achieving an outstanding performance. They are used to choose the best criteria with high priorities by considering other factors. The techniques employ the pairwise comparison matrix of Triangular Fuzzy Number (TFN) calculation to rank the criteria and available alternatives. Also, they are regarded as the best method for solving multi-criteria issues as well as making a selection for the best site of a solar power plant (SPP). Solar radiation is regarded as the highest priority attribute of the fuzzy techniques. In determining the weight of different criteria from linguistic evaluation by different experts, the FAHP is suitable and can be employed. | Easy to use when compared to other methods/can be easily understood/can capture subjective and objective measurements of variables | There is consistency of results with expert judgement/can be subject to inconsistency in judgement and ranking criteria/can become computationally complex to implement | Lee et al. [111]; Liu et al. [114]; Valipour et al. [115]; [116] |

**Table 5.** *Cont.*

| Fuzzy Logic Technique | Type of Application | Brief Discussion | Advantages of FLT | Disadvantages of FLT | References |
|---|---|---|---|---|---|
| ANFIS | PV standalone and latent heat storage systems and solar farms. | The ANFIS was introduced to improve the learning capabilities of ANN, thereby obtaining more accurate approximations. It is said to be a multilayer neural network with the aim of mapping non-linear or models that relate inputs to output values. Considering the quantitative analysis of the ANFIS, it deals with performance measurement using statistical metrics ($R^2$, RMSE, and MAPE). The application of ANFIS to model solar energy systems provides greater accuracy, flexibility, and superior predictive capability compared to other traditional models. ANFIS has the potential to optimize the design and operation as well as enhance system performance and efficiency of solar energy applications such as latent heat storage systems, thereby resulting in greater energy efficiency and cost savings. The objective of ANFIS is to lessen the difference between the actual and desired value through optimizing its parameters. In a solar farm, the ANFIS provides coherent approximations per potential location. | It can solve problems both linear and non-linear/has learning capabilities, and pattern matching. Provides accelerated learning capacity and adaptive interpretation essential to model complex patterns | Loss of interpretability in larger units/high computational expense, and complexity. Need to select an appropriate membership function. | Arulmurugan and Suthanthiravanitha [117]; Sallah et al. [118]; Jagirdar et al. [119]; Tavana et al. [120]; Chekired et al. [121] |

**Table 5.** *Cont.*

| Fuzzy Logic Technique | Type of Application | Brief Discussion | Advantages of FLT | Disadvantages of FLT | References |
| --- | --- | --- | --- | --- | --- |
| Fuzzy MCDM | Solar thermal plant, PV-technology | Considering the qualitative and quantitative analysis of the techniques, this involves linguistic evaluation of subjective criteria, such as the socio-political factors and expert opinions for the qualitative analysis. On the contrary, the quantitative analysis focuses on the numerical data and objective criteria (solar irradiation and cost) to rank alternatives. With the aid of fuzzy MCDM, it was reported that the evaluation index of the solar thermal plant was established. Solar energy technologies experience uncertainties because of the increasing complexity of problems associated with energy policy and decision-making. To address this problem, the fuzzy MCDM is an analytic and effective approach to employ. Similarly, the technique has facilitated identifying the importance of different energy alternatives, scenario analysis, schemes, and decisions based on the plans and investments of projects. | Essentially applicable for solar energy site selection and evaluating its resources and technology. Hence, assist in determining energy policy and investment. | Experiences difficulties in result validation of solar energy data due to inherent fuzziness, as well as increased complexity and computational demands | Wu et al. [99]; Kaya et al. [122]; |

**Table 5.** *Cont.*

| Fuzzy Logic Technique | Type of Application | Brief Discussion | Advantages of FLT | Disadvantages of FLT | References |
|---|---|---|---|---|---|
| Fuzzy TOPSIS and VIKOR | Solar dish Stirling engine, solar PV | The fuzzy TOPSIS and VIKOR provide both quantitative (cost) and qualitative (environmental impact) analysis in relation to solar energy selection and project evaluation of the technology. In solar dish, Stirling engine, and other elements in the solar energy sector, the techniques help to handle the ambiguity and subjectivity of expert opinions and linguistic terms. Furthermore, it helps to select the best opinions on various solar energy technologies. A study on the solar dish Stirling engine reported a maximum error of output power 2.5%; thermal efficiency 8.4% and rate of entropy 6.8% as well as average error of Output power 1.3%; thermal efficiency 4.4% and rate of entropy 3.5% with the employment of fuzzy TOPSIS and VIKOR. Based on the priority of investment, the fuzzy TOPSIS and VIKOR are used for the ordering of alternative solar energy systems. Therefore, findings revealed that solar PV is the paramount renewable energy for investment with reference to the technique's approaches. | Assist in optimizing configuration and decision-making processes. This progresses in handling uncertainties and subjective evaluation of solar energy projects, thereby permitting robust and realistic assessments. | Computationally complex, especially when dealing with a huge number of data/alternatives and criteria. | Ahmadi et al. [123]; Sengul et al. [124]; Taylan et al. [125] |

**Table 5.** *Cont.*

| Fuzzy Logic Technique | Type of Application | Brief Discussion | Advantages of FLT | Disadvantages of FLT | References |
|---|---|---|---|---|---|
| Fuzzy particle swarm optimization (FPSO) | Photovoltaic farms and solar PV systems | The FPSO in relation to solar energy is regarded as a hybrid technique for the optimization of solar energy systems. In this case, it offers quantitative advantages in power output increase, maximum power point tracking, as well as qualitative benefits (improved power quality and stable dynamic conditions). To overcome the limitations of traditional methods, the FPSO provides and offers the combination of adaptive control of fuzzy logic with particle swarm optimization for an efficient and stable approach for solar PV systems. From the simulation result of the design and evaluation of FPSO-based MPPT on PV system, it was revealed that FPSO based MPPT was 14% and 30% faster under partial shading conditions on average and uniform irradiation, respectively, than the settling time using the conventional method. In a development, it was revealed that Sugeno fuzzy logic control plus PSO was a smart renewable energy source to contribute to the frequency stabilizing service in the smart grid. Comparing FPSO with other models, the techniques have a higher degree of accuracy than the Fuzzy -GA model. | Addresses the challenges of balancing exploration and exploitation in optimization problems to enhance convergence speed and solution accuracy with robustness | Presence of potential for premature convergence, sensitivity to parameter turning, and complexity in implementation in relation to solar energy | Sangawong and Ngamroo [126]; Ibrahim et al. [127]; Guo et al. [128] |

**Table 5.** *Cont.*

| Fuzzy Logic Technique | Type of Application | Brief Discussion | Advantages of FLT | Disadvantages of FLT | References |
|---|---|---|---|---|---|
| Fuzzy genetic algorithms (Fuzzy- GA) | Solar radiation; solar PV system | With respect to the solar energy system, the fuzzy GA combines fuzzy logic to handle inherent uncertainties in a qualitative manner and deals with the quantitative aspect, focusing on genetic algorithms to find optimal solutions. The measurable outcomes, such as power loss, energy generation, and power voltage, for example, are quantitatively analyzed by Fuzzy GA for solar energy systems, while, on the contrary, incorporating expert judgement, subjective criteria, and linguistic variables with fuzzy logic to improve decision-making (site or technology) selection is regarded as the qualitative analysis of the technique. A study revealed that the fuzzy GA is superior and performs better than the optimal ANN model in estimating solar radiation. In another study, the techniques were used to choose the best configuration with the lowest cost for the techno-economic optimization of a standalone PV system. | Improve the decision-making process, thereby producing better resource management and a reduction in operational inefficiencies. This fosters increased adaptability to changing conditions. | High cost and complexity of the implementation of solar energy data modelling | Kisi [129]; Erdogdu et al. [130]; Benmouiza et al. [131] |

**Table 5.** *Cont.*

| Fuzzy Logic Technique | Type of Application | Brief Discussion | Advantages of FLT | Disadvantages of FLT | References |
| --- | --- | --- | --- | --- | --- |
| Fuzzy optimization | PV water pumping system | To prevent the errors associated with conventional methods regarding the generation scheduling problems of solar energy systems, the fuzzy optimization technique is employed for this purpose. In this case, the technique is known to have the feature associated with generation scheduling, such as forecasting hourly load and solar radiation errors. These are considered using the fuzzy set to obtain an optimal generation schedule under a certain environment. Interestingly, the technique involves quantitative analysis of complex factors via linguistic terms and fuzzy numbers. This is essential to model uncertainty and achieve precise numerical outcomes. On the contrary, the qualitative analysis of the techniques provides key factors used for the model, such as technical, environmental, and economic aspects. In this case, it assists in guiding the selection of criteria. It is reported that fuzzy optimization has a good performance in terms of global efficiency, as well as optimizing the output power of the system. | Improved solar energy output and accuracy through the optimization of the tilt angle monthly | High computational overhead as well as a lack of experimental validation, and no real-time adaptability to changing environmental impact | Benlarbi et al. [132]; Guler et al. [133]; Liang and Liao [134] |

**Table 5.** *Cont.*

| Fuzzy Logic Technique | Type of Application | Brief Discussion | Advantages of FLT | Disadvantages of FLT | References |
| --- | --- | --- | --- | --- | --- |
| Fuzzy c-means clustering (FCM) | Solar radiation; solar PV system | In terms of quantitative and qualitative analysis of the techniques, the quantitative focus is on the numerical data. Here, the observation consists of n measured variables grouped into an n-dimensional column. The qualitative aspect of the technique deals with the categorical data. Conversely, the technique was employed to extract useful information from hourly solar radiation for optimal standalone PV system sizing with an inclination angle equal to 32°. Therefore, the simulation revealed that the sizing in the hourly solar radiation scale of capacity of the PV panel array ($C_A$) and total component cost ($C_C$) of 0.91 and 3.2 gives a better result than the daily solar radiation scale of 1.09 ($C_A$) and 4.4 ($C_S$), respectively. In another study related to solar radiation, the techniques show a good modelling accuracy despite the spatially and temporary independent data of the training and testing data of the proposed model. | For the effective and efficient determination of the best location for the installation of solar power plants in unproductive areas | Limited to single feature input data/their robustness to noise and effectiveness depend on crucial parameters. Difficult to find the optimal value, which is usually experimentally selected | Almaraashi [135]; de Barros et al. [136]; Memon and Lee [137]; Benmouiza et al. [131]; Kaushik and Hermanta [138] |

**Table 6.** Advantages and limitations of fuzzy logic techniques in relation to solar energy systems.

| Advantages of Fuzzy Logic Techniques to Solar Energy Systems | Limitations of Fuzzy Logic to Solar Energy Systems |
| --- | --- |
| FL is an effective tool for the handling of spatial data from GIS, simulation, and index data from reliability models to identify potential sites for the solar installation on building rooftops, especially at large-scale solar farms. | The FL may require extensive or large solar energy data for optimization and development of complex models. This is due to computational complexity because of multiple calculations for fuzzification, inference, and defuzzification. |
| It is used to reduce the cost of solar energy, thereby creating an adaptable control system that can optimize energy usage, battery management that results in lower electricity bills, peak demand reduction, and improved battery efficiency. | The techniques lack transparency in the decision model, thereby resulting in hindrances to the adoption of solar energy industries. |
| Provides a better result in terms of maximum power point tracking in solar energy systems by providing fast and stable responses. It also handles the non-linear nature of PV systems as well as strong robustness against changes in solar irradiance. | With the potential of the FL techniques, its reliance on thermal imagery restricts the capacity to identify faults in solar energy technologies that do not exhibit thermal characteristics. This is because the technique depends on thermal data to respond to changes in temperature. |
| With FL, higher precision of the accuracy of solar energy data is produced, as well as better prediction modelling capability. This is important in optimizing solar panel performance and efficiency. | Careful design and control strategies are required for the implementation of fuzzy logic techniques, which are complex in solar energy applications. However, FL application in solar energy requires precise modelling and significant fuzzy rules. Therefore, extensive knowledge and expertise are required for its optimal performance. |
| FL enhances solar energy systems by improving efficiency through intelligent power management. This ensures and provides improved stability and better adaptability to changing weather conditions in solar energy systems. | Fuzzy logic is said to struggle in terms of predicting the future demand of solar energy. This is because it is computationally complex, especially with large and uncertain imprecise datasets from the measurement of selected solar energy, such as solar radiation, angle of incidence, and tilt of solar PV modules via a data acquisition system. |

## 7. Solar Energy Challenges with a Possible Solution via Fuzzy Logic Technique

The challenges of solar energy can be classified into three stages: evaluation/diagnosis, installation, and operation. The evaluation/diagnosis stage consists of the process/system modelling, evaluation/assessment, and prediction/forecasting of the solar energy system. On the other hand, the operation stage consists of the management and maintenance. Table 7 shows the stages associated with the challenges of solar energy systems and their possible solutions using fuzzy logic.

**Table 7.** Challenges of solar energy systems and their possible solutions via FL.

| Solar Energy Challenges | Factor Responsible | Possible Solution via FL | Aim or Purpose |
| --- | --- | --- | --- |
| Evaluating and assessing solar energy systems. | Technical/economic and environmental considerations. | Fuzzy ANP and AHP/MCDM/Fuzzy Delphi/ANFIS/Grey AHP/TOPSIS and VIKOR. | To determine the most eligible solar energy technology for investment. To rank the weights of the criteria as well as to select the best option for a particular solar energy system. To evaluate and assess solar energy systems. |

**Table 7.** *Cont.*

| Solar Energy Challenges | Factor Responsible | Possible Solution via FL | Aim or Purpose |
|---|---|---|---|
| Prediction and forecasting of solar energy systems. | Weather and geographical variability/data requirement/ | Fuzzy c—means/ANFIS/Fuzzy ANN/Fuzzy SVM/TOPSIS/Neuro fuzzy system. | To predict the best position for the installation of solar energy plants, as well as solar radiation, and to optimize the performance of the system. To forecast the solar radiation and detect faults in the system |
| Process and modelling of solar energy systems. | Sunlight variability/energy storage limitations and complexities of grid integration. | ANFIS/Fuzzy GA/Fuzzy ANN/Fuzzy PSO/ANFIS controller/Fuzzy logic controller. | To optimize and enhance the modelling and control of the solar energy systems. To handle tasks in relation to maximum power point tracking (MPPT) and energy management, as well as improving solar energy output. |
| Management and maintenance of solar energy systems. | Skilled personnel/ high upfront cost/intermittent power generation. | ANFIS and Fuzzy ANN. | To improve the performance of a standalone solar energy system, as well as provide high accuracy and reliability for its performance through prediction. |

## 8. Technological Development Trends and Application Prospect

The development trends of fuzzy logic and its application prospects include energy management systems (EMS), MPPT, demand side management (DSM), microgrids and off-grid systems, and smart home and building energy management. The EMS decision-making process is carried out by a fuzzy logic controller (FLC), which controls the hybrid energy resources by continuously observing the load demand, battery charging, and discharging conditions. This is to regulate the system power without cutting off the load supply [139]. With the aid of MATLAB Simulink, the battery energy storage system (ESS) in a microgrid is charged and discharged using the fuzzy logic-based EMS [140]. According to Subudhi and Pradhan [141], varieties of MPPT algorithms have been developed to maximize solar PV system power output. Some of these typical methods include the constant velocity (CV) [142], ANN [143], P&O [144], incremental conductance (IC) [145], and fuzzy logic control (FLC) [146]. In comparison, the MPPT techniques provide better tracking accuracy and have a high computational cost. For the battery-powered hybrid systems, stability is being increased with better change controllers [147]. It is interesting to mention that, generally, the development trends and application prospects of fuzzy logic seen in solar energy systems improve the effectiveness and efficiency of managing and handling ambiguous data as well as uncertainty behaviour [148]. The DSM stresses the efficiency of energy use, whereas the supply side management (SSM) deals with energy generation and delivery [149]. Demand response (DR) is a crucial element of the DSM, which allows users to modify their electricity consumption in response to supply conditions or price changes, thereby lowering the cost and improving grid reliability [139]. The integration of a grid-connected renewable energy system at the household level impacts the power quality and distribution network stability. This is said to be driven by the growth of residential smart microgrids [150]. To this effect, several energy-management strategies have been developed to balance the microgrid's generation and consumption, thereby minimizing the user inference and reducing the cost of energy through shifting the load during the off-peak hours [151]. To reduce transmission losses, Livengood and Larson [152] mentioned that peak demand and the requirement for backup solar power plants help the grid. With the application of solar energy with respect to the solar microgrid, its energy management is of two types, namely the rule-based techniques (fuzzy or deterministic) and the optimization method. For rule-based methods, the fuzzy logic controller is commonly employed because of its capability to manage non-linearities without the need for intricate mathematical models [153]. Solar energies are often used in smart homes [154]; however, how the energy is captured, used, or stored determines how sustainable they are [155]. Therefore, to integrate a hybrid-battery energy management system, Zhang et al. [156] proposed a fuzzy expert system for efficient smart-home management (FES-ESHMS). The findings show that by increasing the energy efficiency and reducing overall cost, smart homes with solar microgrids achieve larger smart grids (SG) and demand side management (DSM) side objectives. The advantage is that the system improves the dependability, user comfort, and energy sustainability as part of the development of smart cities [156].

## 9. Conclusions, Limitations, and Recommendations

This paper reviews the fuzzy logic techniques with an emphasis on solar energy systems. One benefit of the study deals with the potential contribution in promoting the application of fuzzy logic techniques as an aspect of methodologies employed in solar energy systems. Having looked at the advantages and disadvantages of FL, this provides a guide to the decision makers and stakeholders to select and implement an appropriate and suitable fuzzy logic method for solar energy projects. The reviews address the concern and demonstrate the possible challenges of solar energy systems and projects, with a possible solution of employing fuzzy logic to improve their performance. Fuzzy logic techniques, in relation to solar energy processes, deal with fuzzy models (for predicting solar energy systems), hybrid models (simulating the system's performance), and MCDM for testing numerical and simulation purposes. According to the study, these are necessary for the decision-making model, ranking of alternative criteria and weight, and assessing the potential location for the installation of solar energy plants. The development and implementation of relevant policies need to be established to promote and improve the adoption of fuzzy logic techniques in the solar energy field and its related industries and sectors. Training programmes need to be mapped out and established to educate the stakeholders in the PV solar energy industry about the importance and relevance of fuzzy logic techniques. Government, industries, research bodies, and institutions need to fund research and development as well as projects in relation to the promotion of the use of fuzzy logic techniques in PV solar energy, especially as it concerns academic research and industry collaboration. Importantly, for the efficient and effective performance of solar energy systems, the integration or incorporation of fuzzy logic and neural networks is recommended.

### *9.1. Practical Implications of the Study*

From the review findings, the technique evidently provides a better optimization of energy output in real-world scenarios because of its intelligent maximum power point tracking (MPPT) and its adjustment of tilt angle during the design of solar energy systems, managing the intermittent nature of solar power as well as improving the resilience of solar energy via adaptive control. This is especially important in solar energy industries, such as photovoltaic energy, solar farms, and solar thermal heating systems. Also, in solar battery (hybrid) industries, the study facilitates the optimal performance of energy management

### *9.2. Future Studies/Direction*

Looking ahead, future studies should focus on the integration of fuzzy logic with the multi-goal programming model, as well as conduct studies to address the limitations associated with the resources of time and cost. In enhancing fault detection and classification in PV systems based on a fuzzy logic algorithm, there is a need to integrate complementary diagnostic methods to broaden the spectrum of detectable faults. Through this, the robustness of fault detection across various conditions of PV panels is enhanced. Further research could also explore the combination of fuzzy logic with other algorithms in relation to a particular solar energy technology as a hybrid optimization technique. The study will focus on dynamically adjusting fuzzy rules and controlling the threshold based on the performance feedback of the solar energy system.

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## References

1. Deshmukh, M.K.; Sameeroddin, M.; Abdul, D.; Sattar, M.A. Renewable energy in the 21st century: A review. *Mater. Today Proc.* **2023**, *80*, 1756–1759. [CrossRef]
2. Boyle, A.E.; Redgwell, C. *Birnie, Boyle, and Redgwell's International Law and the Environment*; Oxford University Press: Oxford, UK, 2021.
3. Olabi, A.G.; Abdelkareem, M.A. Renewable energy and climate change. *Renew. Sustain. Energy Rev.* **2022**, *158*, 112111. [CrossRef]
4. Sattar, M.A.; Sameeroddin, M.; Deshmukh, M.K.; Sami, M.A. Renewable energy and its industrial applications. *Int. Res. J. Eng. Technol. (IRJET 2020)* **2020**, *7*, 6042–6046.
5. Petrović-Ranđelović, M.; Kocić, N.; Stojanović-Ranđelović, B. The importance of renewable energy sources for sustainable development. *Econ. Sustain. Dev* **2020**, *4*, 15–24. [CrossRef]
6. Alhamrouni, I.; Danial, M.; Salem, M.; Awalin, L.J.; Ismail, B. Design of 2LC-Y DC-DC converter for high voltage/low current renewable energy application. *Test Eng. Manag.* **2020**, *83*, 2111–2117.
7. Alhafadhi, L.; Teh, J.; Lai, C.M.; Salem, M. Predictive adaptive filter for reducing total harmonics distortion in PV systems. *Energies* **2020**, *13*, 3286. [CrossRef]
8. Bughneda, A.; Salem, M.; Richelli, A.; Ishak, D.; Alatai, S. Review of multilevel inverters for PV energy system applications. *Energies* **2021**, *14*, 1585. [CrossRef]
9. Ang, T.Z.; Salem, M.; Kamarol, M.; Das, H.S.; Nazari, M.A.; Prabaharan, N. A comprehensive study of renewable energy sources: Classifications, challenges and suggestions. *Energy Strategy Rev.* **2022**, *43*, 100939. [CrossRef]
10. Cleveland, C.J.; Morris, C.G. (Eds.) *Dictionary of Energy*; Elsevier: Amsterdam, The Netherlands, 2005.
11. Breeze, P. *Power Generation Technologies*; Newnes: Oxford, UK, 2019.
12. Rashad, A.; Kamel, S.; Jurado, F.; Gharehpetian, G.; SM, M. The basic principles of wind farms. In *Distributed Generation Systems: Design, Operation and Grid Integration*; Elsevier: Amsterdam, The Netherlands, 2017; pp. 21–67.
13. Pishvaee, M.M.; Mohseni, S.; Bairamzadeh, S. *Biomass to Biofuel Supply Chain Design and Planning Under Uncertainty*; Elsevier: Amsterdam, The Netherlands, 2021.
14. Belyakov, N. *Bioenergy Sustainable Power Generation*; Academic Press: Cambridge, MA, USA, 2020; pp. 461–474.
15. Sharmina, M.; McGlade, C.; Gilbert, P.; Larkin, A. Global energy scenarios and their implications for future shipped trade. *Mar. Policy* **2017**, *84*, 12–21. [CrossRef]

16. Killingtveit, Å. Hydropower: A Low-Carbon Power Source. In *Advances in Carbon Management Technologies*; CRC Press: Boca Raton, FL, USA, 2020; pp. 433–450.
17. Neill, S.P.; Hashemi, M.R.; Lewis, M.J. Tidal energy leasing and tidal phasing. *Renew. Energy* **2016**, *85*, 580–587. [CrossRef]
18. Waters, S.; Aggidis, G. Tidal range technologies and state of the art in review. *Renew. Sustain. Energy Rev.* **2016**, *59*, 514–529. [CrossRef]
19. Turcotte, D.L.; Schubert, G. *Geodynamics*; Cambridge University Press: Cambridge, NY, USA, 2002.
20. Barbier, E. Geothermal energy technology and current status: An overview. *Renew. Sustain. Energy Rev.* **2002**, *6*, 3–65. [CrossRef]
21. Li, K.; Bian, H.; Liu, C.; Zhang, D.; Yang, Y. Comparison of geothermal with solar and wind power generation systems. *Renew. Sustain. Energy Rev.* **2015**, *42*, 1464–1474. [CrossRef]
22. El Haj Assad, M.; Bani-Hani, E.; Khalil, M.J. Performance of geothermal power plants (single, dual, and binary) to compensate for LHC-CERN power consumption: Comparative study. *Geotherm. Energy* **2017**, *5*, 17. [CrossRef]
23. International Energy Agency. *World Energy Outlook*; OECD/IEA: Paris, France, 2009.
24. Suganthi, L.; Iniyan, S.; Samuel, A.A. Applications of fuzzy logic in renewable energy systems—A review. *Renew. Sustain. Energy Rev.* **2015**, *48*, 585–607. [CrossRef]
25. Kedir, N.; Nguyen, P.H.; Pérez, C.; Ponce, P.; Fayek, A.R. Systematic literature review on fuzzy hybrid methods in photovoltaic solar energy: Opportunities, challenges, and guidance for implementation. *Energies* **2023**, *16*, 3795. [CrossRef]
26. Rubio, F.R.; Berenguel, M.; Camacho, E.F. Fuzzy logic control of a solar power plant. *IEEE Trans. Fuzzy Syst.* **1995**, *3*, 459–468. [CrossRef]
27. Patel, D.; Patel, S.; Patel, P.; Shah, M. Solar radiation and solar energy estimation using ANN and Fuzzy logic concept: A comprehensive and systematic study. *Environ. Sci. Pollut. Res.* **2022**, *29*, 32428–32442. [CrossRef]
28. Srilakshmi, K.; Sundaragiri, D.; Gaddameedhi, S.; Vangalapudi, R.; Balachandran, P.K.; Colak, I.; Selvarajan, S. Simulation of grid/standalone solar energy supplied reduced switch converter with optimal fuzzy logic controller using golden BallAlgorithm. *Front. Energy Res.* **2024**, *12*, 1370412. [CrossRef]
29. Patino, C.M.; Ferreira, J.C. Inclusion and exclusion criteria in research studies: Definitions and why they matter. *J. Bras. Pneumol.* **2018**, *44*, 84. [CrossRef]
30. Zenani, S.; Obileke, K.; Ndiweni, O.; Mukumba, P. A Review of the Application of Fuzzy Logic in Bioenergy Technology. *Processes* **2025**, *13*, 2251. [CrossRef]
31. Smela, B.; Toumi, M.; Świerk, K.; Francois, C.; Biernikiewicz, M.; Clay, E.; Boyer, L. Rapid literature review: Definition and methodology. *J. Mark. Access Health Policy* **2023**, *11*, 2241234. [CrossRef]
32. Maka, A.O.; Alabid, J.M. Solar energy technology and its roles in sustainable development. *Clean Energy* **2022**, *6*, 476–483. [CrossRef]
33. Panwar, N.L.; Kaushik, S.C.; Kothari, S. Role of renewable energy sources in environmental protection: A review. *Renew. Sustain. Energy Rev.* **2011**, *15*, 1513–1524. [CrossRef]
34. Nozik, A.J. Photoelectrochemistry: Applications to solar energy conversion. *Annu. Rev. Phys. Chem.* **1978**, *29*, 189–222. [CrossRef]
35. Kannan, N.; Vakeesan, D. Solar energy for future world: -A review. *Renew. Sustain. Energy Rev.* **2016**, *62*, 1092–1105. [CrossRef]
36. Khamooshi, M.; Salati, H.; Egelioglu, F.; Hooshyar Faghiri, A.; Tarabishi, J.; Babadi, S. A review of solar photovoltaic concentrators. *Int. J. Photoenergy* **2014**, *2014*, 958521. [CrossRef]
37. Pérez-Higueras, P.; Muñoz, E.; Almonacid, G.; Vidal, P.G. High Concentrator PhotoVoltaics efficiencies: Present status and forecast. *Renew. Sustain. Energy Rev.* **2011**, *15*, 1810–1815. [CrossRef]
38. El Bassam, N.; Schlichting, M.; Pagani, D. (Eds.) *Distributed Renewable Energies for Off-Grid Communities: Empowering a Sustainable, Competitive, and Secure Twenty-First Century*; Elsevier: Amsterdam, The Netherlands, 2021.
39. Butler, B.A.; Van Dyk, E.E.; Vorster, F.J.; Okullo, W.; Munji, M.K.; Booysen, P. Characterization of a low concentrator photovoltaics module. *Phys. B Condens. Matter* **2012**, *407*, 1501–1504. [CrossRef]
40. Ejaz, A.; Babar, H.; Ali, H.M.; Jamil, F.; Janjua, M.M.; Fattah, I.R.; Said, Z.; Li, C. Concentrated photovoltaics as light harvesters: Outlook, recent progress, and challenges. *Sustain. Energy Technol. Assess.* **2021**, *46*, 101199. [CrossRef]
41. Borghesi, A.; Guizzetti, G.; Palik, E.D. *Handbook of Optical Constants of Solids II*; Academic Press: Cambridge, MA, USA, 1991.
42. Gilman, J.M.; O'Neill, A.G. Device applications of interband tunneling structures with one, two, and three dimensions. *J. Appl. Phys.* **1993**, *74*, 351–358. [CrossRef]
43. King, R.R.; Law, A.; Edmondson, K.M.; Fetzer, C.M.; Kinsey, G.S.; Yoon, H.; Sherif, R.A.; Karam, N.H. 40% efficient metamorphic GaInP/GaInAs/Ge multijunction solar cells. *Appl. Phys. Lett.* **2007**, *90*, 183516. [CrossRef]
44. Olson, J.M.; Kurtz, S.R.; Kibbler, A.E.; Faine, P. A 27.3% efficient Ga0. 5In0. 5P/GaAs tandem solar cell. *Appl. Phys. Lett.* **1990**, *56*, 623–625. [CrossRef]
45. Araki, K.; Yamaguchi, M.; Takamoto, T.; Ikeda, E.; Agui, T.; Kurita, H.; Takahashi, K.; Unno, T. Characteristics of GaAs-based concentrator cells. *Sol. Energy Mater. Sol. Cells* **2001**, *66*, 559–565. [CrossRef]

46. Soley, S.S.; Dwivedi, A.D. Numerical simulation and performance analysis of InGaP, GaAs, Ge single junction and InGaP/GaAs/Ge triple junction solar cells. *Mater. Today Proc.* **2021**, *39*, 2050–2055. [CrossRef]
47. Cazzaniga, R.; Cicu, M.; Rosa-Clot, M.; Rosa-Clot, P.; Tina, G.M.; Ventura, C. Floating photovoltaic plants: Performance analysis and design solutions. *Renew. Sustain. Energy Rev.* **2018**, *81*, 1730–1741. [CrossRef]
48. IEA. *PVPS Annual Report 2014*; IEA: Paris, France, 2014.
49. Trapani, K.; Redón Santafé, M. A review of floating photovoltaic installations: 2007–2013. *Prog. Photovolt. Res. Appl.* **2015**, *23*, 524–532. [CrossRef]
50. Alam, M.Z.; Ohgaki, S. Evaluation of UV-radiation and its residual effect for algal growth control. In *Advances in Water and Wastewater Treatment Technology*; Elsevier Science BV: Amsterdam, The Netherlands, 2001; pp. 109–117.
51. Rosa-Clot, M.; Tina, G.M. *Submerged and Floating Photovoltaic Systems: Modelling, Design and Case Studies*; Academic Press: Cambridge, MA, USA, 2017.
52. E. Ministry of Trade, International Energy Agency. *The World's Largest Floating Photovoltaic Business in Saemangeum*; E. Ministry of Trade, International Energy Agency: Sejong City, Republic of Korea, 2019.
53. Wegh, R.T.; Donker, H.; Oskam, K.D.; Meijerink, A. Visible quantum cutting in LiGdF4: Eu3+ through downconversion. *Science* **1999**, *283*, 663–666. [CrossRef]
54. Richards, B.S. Enhancing the performance of silicon solar cells via the application of passive luminescence conversion layers. *Sol. Energy Mater. Sol. Cells* **2006**, *90*, 2329–2337. [CrossRef]
55. De Vos, A.; Szymanska, A.; Badescu, V. Modelling of solar cells with down-conversion of high energy photons, anti-reflection coatings and light trapping. *Energy Convers. Manag.* **2009**, *50*, 328–336. [CrossRef]
56. Wang, Y.; Wang, S.; Zhang, Y.; Mao, Q.; Su, S.; Chen, Z. Enhancing efficiencies of solar thermophotovoltaic cells by downconversion of high-energy photons. *J. Renew. Sustain. Energy* **2021**, *13*, 033501. [CrossRef]
57. Khanjari, Y.; Pourfayaz, F.; Kasaeian, A.B. Numerical investigation on using of nanofluid in a water-cooled photovoltaic thermal system. *Energy Convers. Manag.* **2016**, *122*, 263–278. [CrossRef]
58. Khanjari, Y.; Kasaeian, A.B.; Pourfayaz, F. Evaluating the environmental parameters affecting the performance of photovoltaic thermal system using nanofluid. *Appl. Therm. Eng.* **2017**, *115*, 178–187. [CrossRef]
59. Suresh, A.K.; Khurana, S.; Nandan, G.; Dwivedi, G.; Kumar, S. Role on nanofluids in cooling solar photovoltaic cell to enhance overall efficiency. *Mater. Today Proc.* **2018**, *5*, 20614–20620. [CrossRef]
60. Conibeer, G.; Shrestha, S.; Huang, S.; Patterson, R.; Xia, H.; Feng, Y.; Zhang, P.; Gupta, N.; Tayebjee, M.; Smyth, S.; et al. Hot carrier solar cell absorbers: Materials, mechanisms and nanostructures. In *Next Generation Technologies for Solar Energy Conversion V*; SPIE: Sydney, Australia, 2014; Volume 9178, p. 917802.
61. Ross, R.T.; Nozik, A.J. Efficiency of hot-carrier solar energy converters. *J. Appl. Phys.* **1982**, *53*, 3813–3818. [CrossRef]
62. Green, M.A. Third generation photovoltaics: Ultra-high conversion efficiency at low cost. *Prog. Photovolt. Res. Appl.* **2001**, *9*, 123–135. [CrossRef]
63. Conibeer, G. Third-generation photovoltaics. *Mater. Today* **2007**, *10*, 42–50. [CrossRef]
64. Bhatia, S.C. Solar thermal energy. In *Advanced Renewable Energy Systems*; DelhiBhatia, S.C., Ed.; Woodhead Publish-ing India: Delhi, India, 2014; pp. 94–143.
65. Chang, C.; Wang, Z.; Fu, B.; Ji, Y. High-efficiency solar thermoelectric conversion enabled by movable charging of molten salts. *Sci. Rep.* **2020**, *10*, 20500. [CrossRef]
66. Mellit, A.; Kalogirou, S.A. Machine learning and deep learning for photovoltaic applications. In *Artificial Intelligence for Smart Photovoltaic Technologies*; AIP Publishing LLC: Melville, NY, USA, 2022; Volume 1.
67. Kumari, P.; Toshniwal, D. Analysis of ANN-based daily global horizontal irradiance prediction models with different meteorological parameters: A case study of mountainous region of India. *Int. J. Green Energy* **2021**, *18*, 1007–1026. [CrossRef]
68. Kazem, H.A.; Chaichan, M.T.; Al-Waeli, A.H.; Gholami, A. A systematic review of solar photovoltaic energy systems design modelling, algorithms, and software. *Energy Sources Part A Recovery Util. Environ. Eff.* **2022**, *44*, 6709–6736. [CrossRef]
69. Nur Farhana Akhter, N.F.; Talukder, M.J. Python-Based Hybrid AI Models for Real-Time Grid Stability Analysis In Solar Energy Networks. *Innov. Eng. J.* **2024**, *1*, 10–70937.
70. Jailani, N.L.; Dhanasegaran, J.K.; Alkawsi, G.; Alkahtani, A.A.; Phing, C.C.; Baashar, Y.; Capretz, L.F.; Al-Shetwi, A.Q.; Tiong, S.K. Investigating the power of LSTM-based models in solar energy forecasting. *Processes* **2023**, *11*, 1382. [CrossRef]
71. Elsheikh, A.H.; Sharshir, S.W.; Abd Elaziz, M.; Kabeel, A.E.; Guilan, W.; Haiou, Z. Modeling of solar energy systems using artificial neural network: A comprehensive review. *Sol. Energy* **2019**, *180*, 622–639. [CrossRef]
72. Saatchi, R. Fuzzy logic concepts, developments and implementation. *Information* **2024**, *15*, 656. [CrossRef]
73. Zadeh, L.A. (Ed.) Fuzzy logic, neural networks, and soft computing. In *Fuzzy Sets, Fuzzy Logic, and Fuzzy Systems: Selected Papers by Lotfi A Zadeh*; State University of New York: Binghamton, NY, USA, 1996; pp. 775–782.
74. Shimura, M. Fuzzy sets concept in rank-ordering objects. *J. Math. Anal. Appl.* **1973**, *43*, 717–733. [CrossRef]
75. Das, R.; Sen, S.; Maulik, U. A survey on fuzzy deep neural networks. *ACM Comput. Surv. (CSUR)* **2020**, *53*, 1–25. [CrossRef]

76. Grabisch, M. Fuzzy integral in multicriteria decision making. *Fuzzy Sets Syst.* **1995**, *69*, 279–298. [CrossRef]
77. Murofushi, T.; Sugeno, M. *Fuzzy Measures and Integrals: Theory and Applications*; Physical-Verlag: Heidelberg, Germany, 2000.
78. Liginlal, D.; Ow, T.T. Modeling attitude to risk in human decision processes: An application of fuzzy measures. *Fuzzy Sets Syst.* **2006**, *157*, 3040–3054. [CrossRef]
79. Plerou, A.; Vlamou, E.; Papadopoulos, V. Fuzzy genetic algorithms: Fuzzy logic controllers and genetic algorithms. *Glob. J. Res. Anal.* **2016**, *5*, 497–500.
80. Hsu, Y.L.; Lee, C.H.; Kreng, V.B. The application of Fuzzy Delphi Method and Fuzzy AHP in lubricant regenerative technology selection. *Expert Syst. Appl.* **2010**, *37*, 419–425. [CrossRef]
81. Chou, T.Y.; Liang, G.S.; Han, T.C. Application of fuzzy regression on air cargo volume forecast. *Qual. Quant.* **2011**, *45*, 1539–1550. [CrossRef]
82. Deng, J.L. Properties of multivariable grey model GM (1, N). *J. Grey Syst.* **1989**, *1*, 25–41.
83. Wong, C.C.; Liang, W.C.; Feng, H.M.; Chiang, D.A. Grey prediction controller design. *J. Grey Syst.* **1998**, *10*, 123–131.
84. Wang, Y.F. Predicting stock price using fuzzy grey prediction system. *Expert Syst. Appl.* **2002**, *22*, 33–38. [CrossRef]
85. Rusnedy, H.; Iswavigra, D.U.; Pranggono, B.; Haerani, E.; Saktioto, T. Decision support system for smartphone recommendation: The comparison of fuzzy AHP and fuzzy ANP in multi-attribute decision making. *Sinergi* **2021**, *25*, 101–110.
86. Khoshnevisan, B.; Rafiee, S.; Omid, M.; Mousazadeh, H.; Shamshirband, S.; Ab Hamid, S.H. Developing a fuzzy clustering model for better energy use in farm management systems. *Renew. Sustain. Energy Rev.* **2015**, *48*, 27–34. [CrossRef]
87. Paulescu, M.; Gravila, P.; Tulcan-Paulescu, E. Fuzzy logic algorithms for atmospheric transmittances of use in solar energy estimation. *Energy Convers. Manag.* **2008**, *49*, 3691–3697. [CrossRef]
88. Walia, N.; Singh, H.; Sharma, A. ANFIS: Adaptive neuro-fuzzy inference system-a survey. *Int. J. Comput. Appl.* **2015**, *123*, 32–38. [CrossRef]
89. Rajasekar, V.; Predić, B.; Saracevic, M.; Elhoseny, M.; Karabasevic, D.; Stanujkic, D.; Jayapaul, P. Enhanced multimodal biometric recognition approach for smart cities based on an optimized fuzzy genetic algorithm. *Sci. Rep.* **2022**, *12*, 622. [CrossRef]
90. Sagar, L.K.; Das, D.B. Fuzzy expert system for determining state of solar photo voltaic power plant based on real-time data. *Evergreen* **2022**, *9*, 870–880. [CrossRef]
91. Zhang, M. Design and implementation of industrial robot path planning based on fuzzy decision support system. *Eng. Res. Express* **2025**, *7*, 025207. [CrossRef]
92. Arana-Jiménez, M.; Sánchez-Gil, M.C.; Lozano, S. A fuzzy DEA slacks-based approach. *J. Comput. Appl. Math.* **2022**, *404*, 113180. [CrossRef]
93. Kumar, R.; Padhi, S.S.; Sarkar, A. Supplier selection of an Indian heavy locomotive manufacturer: An integrated approach using Taguchi loss function, TOPSIS, and AHP. *IIMB Manag. Rev.* **2019**, *31*, 78–90. [CrossRef]
94. Jiskani, I.M.; Cai, Q.; Zhou, W.; Lu, X.; Shah, S.A. An integrated fuzzy decision support system for analyzing challenges and pathways to promote green and climate smart mining. *Expert Syst. Appl.* **2022**, *188*, 116062. [CrossRef]
95. Wang, K.F.; An, J.; Wei, Z.; Cui, C.; Ma, X.H.; Ma, C.; Bao, H.Q. Deep learning-based imbalanced classification with fuzzy support vector machine. *Front. Bioeng. Biotechnol.* **2022**, *9*, 802712. [CrossRef]
96. Stepanenko, V.A.; Zamulko, A.I.; Veremiichuk, Y.A. Fuzzy logic in the decision-making tasks of connecting renewable energy sources into the electricity supply system. *IOP Conf. Ser. Earth Environ. Sci.* **2023**, *1254*, 012043. [CrossRef]
97. Mamlook, R.; Akash, B.A.; Nijmeh, S. Fuzzy sets programming to perform evaluation of solar systems in Jordan. *Energy Convers. Manag.* **2001**, *42*, 1717–1726. [CrossRef]
98. Charabi, Y.; Gastli, A. PV site suitability analysis using GIS-based spatial fuzzy multi-criteria evaluation. *Renew. Energy* **2011**, *36*, 2554–2561. [CrossRef]
99. Wu, Y.; Geng, S.; Zhang, H.; Gao, M. Decision framework of solar thermal power plant site selection based on linguistic Choquet operator. *Appl. Energy* **2014**, *136*, 303–311. [CrossRef]
100. Zhang, H.; Davigny, A.; Colas, F.; Poste, Y.; Robyns, B. Fuzzy logic-based energy management strategy for commercial buildings integrating photovoltaic and storage systems. *Energy Build.* **2012**, *54*, 196–206. [CrossRef]
101. Zhai, P.; Williams, E.D. Analyzing consumer acceptance of photovoltaics (PV) using a fuzzy logic model. *Renew. Energy* **2012**, *41*, 350–357. [CrossRef]
102. Liu, S.Y.; Perng, Y.H.; Ho, Y.F. The effect of renewable energy application on Taiwan buildings: What are the challenges and strategies for solar energy exploitation? *Renew. Sustain. Energy Rev.* **2013**, *28*, 92–106. [CrossRef]
103. Ishikawa, A.; Amagasa, M.; Shiga, T.; Tomizawa, G.; Tatsuta, R.; Mieno, H. The max-min Delphi method and fuzzy Delphi method via fuzzy integration. *Fuzzy Sets Syst.* **1993**, *55*, 241–253. [CrossRef]
104. D'Souza, N.S.; Lopes, L.A.; Liu, X. Comparative study of variable size perturbation and observation maximum power point trackers for PV systems. *Electr. Power Syst. Res.* **2010**, *80*, 296–305. [CrossRef]

105. D'Souza, N.S.; Lopes, L.A.; Liu, X. Peak current control-based maximum power point trackers for faster transient responses. In Proceedings of the 2006 Canadian Conference on Electrical and Computer Engineering, Ottawa, ON, Canada, 7–10 May 2006; IEEE: Piscataway, NJ, USA, 2006; pp. 659–663.
106. Niapour, S.K.; Danyali, S.; Sharifian, M.B.; Feyzi, M.R. Brushless DC motor drives supplied by PV power system based on Z-source inverter and FL-IC MPPT controller. *Energy Convers. Manag.* **2011**, *52*, 3043–3059. [CrossRef]
107. Chaouachi, A.; Kamel, R.M.; Nagasaka, K. A novel multi-model neuro-fuzzy-based MPPT for three-phase grid-connected photovoltaic system. *Sol. Energy* **2010**, *84*, 2219–2229. [CrossRef]
108. Salah, C.B.; Ouali, M. Comparison of fuzzy logic and neural network in maximum power point tracker for PV systems. *Electr. Power Syst. Res.* **2011**, *81*, 43–50. [CrossRef]
109. Azadeh, A.; Sheikhalishahi, M.; Asadzadeh, S.M. A flexible neural network-fuzzy data envelopment analysis approach for location optimization of solar plants with uncertainty and complexity. *Renew. Energy* **2011**, *36*, 3394–3401. [CrossRef]
110. Azadeh, A.; Ghaderi, S.F.; Maghsoudi, A. Location optimization of solar plants by an integrated hierarchical DEA PCA approach. *Energy Policy* **2008**, *36*, 3993–4004. [CrossRef]
111. Lee, A.H.; Chen, H.H.; Kang, H.Y. A model to analyze strategic products for photovoltaic silicon thin-film solar cell power industry. *Renew. Sustain. Energy Rev.* **2011**, *15*, 1271–1283. [CrossRef]
112. Zeng, Z.; Nasri, E.; Chini, A.; Ries, R.; Xu, J. A multiple objective decision-making model for energy generation portfolio under fuzzy uncertainty: Case study of large-scale investor-owned utilities in Florida. *Renew. Energy* **2015**, *75*, 224–242. [CrossRef]
113. Hernández-Moro, J.; Martinez-Duart, J.M. Analytical model for solar PV and CSP electricity costs: Present LCOE values and their future evolution. *Renew. Sustain. Energy Rev.* **2013**, *20*, 119–132. [CrossRef]
114. Liu, Y.; Eckert, C.M.; Earl, C. A review of fuzzy AHP methods for decision-making with subjective judgements. *Expert Syst. Appl.* **2020**, *161*, 113738. [CrossRef]
115. Valipour, A.; Yahaya, N.; Md Noor, N.; Kildienė, S.; Sarvari, H.; Mardani, A. A fuzzy analytic network process method for risk prioritization in freeway PPP projects: An Iranian case study. *J. Civ. Eng. Manag.* **2015**, *21*, 933–947. [CrossRef]
116. Abdullah, A.G.; Dwitasari, N.A.; Setiorini, A.H.; Hakim, D.L. Comparative analysis of AHP and fuzzy AHP for solar power plant site selection. *J. Eng. Sci. Technol.* **2021**, *16*, 3505–3520.
117. Arulmurugan, R.; Suthanthiravanitha, N.J. Model and design of a fuzzy-based Hopfield NN tracking controller for standalone PV applications. *Electr. Power Syst. Res.* **2015**, *120*, 184–193. [CrossRef]
118. Salleh, M.N.; Talpur, N.; Hussain, K. Adaptive neuro-fuzzy inference system: Overview, strengths, limitations, and solutions. In *Data Mining and Big Data, Proceedings of the International Conference on Data Mining and Big Data, Fukuoka, Japan, 27 July–1 August 2017*; Springer International Publishing: Cham, Switzerland, 2017; pp. 527–535.
119. Jagirdar, M.N.; Priyadarshi, G.; Naik, B.K.; Niyas, H. Implementation of adaptive neuro-fuzzy inference system in design and process optimization of latent heat storage system. *J. Energy Storage* **2024**, *89*, 111810. [CrossRef]
120. Tavana, M.; Arteaga, F.J.; Mohammadi, S.; Alimohammadi, M. A fuzzy multi-criteria spatial decision support system for solar farm location planning. *Energy Strategy Rev.* **2017**, *18*, 93–105. [CrossRef]
121. Chekired, F.; Mellit, A.; Kalogirou, S.A.; Larbes, C. Intelligent maximum power point trackers for photovoltaic applications using FPGA chip: A comparative study. *Sol. Energy* **2014**, *101*, 83–99. [CrossRef]
122. Kaya, I.; Çolak, M.; Terzi, F. A comprehensive review of fuzzy multi criteria decision making methodologies for energy policy making. *Energy Strategy Rev.* **2019**, *24*, 207–228. [CrossRef]
123. Ahmadi, M.H.; Sayyaadi, H.; Dehghani, S.; Hosseinzade, H. Designing a solar powered Stirling heat engine based on multiple criteria: Maximized thermal efficiency and power. *Energy Convers. Manag.* **2013**, *75*, 282–291. [CrossRef]
124. Şengül, Ü.; Eren, M.; Shiraz, S.E.; Gezder, V.; Şengül, A.B. Fuzzy TOPSIS method for ranking renewable energy supply systems in Turkey. *Renew. Energy* **2015**, *75*, 617–625. [CrossRef]
125. Taylan, O.; Alamoudi, R.; Kabli, M.; AlJifri, A.; Ramzi, F.; Herrera-Viedma, E. Assessment of energy systems using extended fuzzy AHP, fuzzy VIKOR, and TOPSIS approaches to manage non-cooperative opinions. *Sustainability* **2020**, *12*, 2745. [CrossRef]
126. Sangawong, N.; Ngamroo, I. Intelligent photovoltaic farms for robust frequency stabilization in multi-area interconnected power system based on PSO-based optimal Sugeno fuzzy logic control. *Renew. Energy* **2015**, *74*, 555–567. [CrossRef]
127. Ibrahim, O.; Aziz, M.J.; Ayop, R.; Dahiru, A.T.; Low, W.Y.; Sulaiman, M.H.; Amosa, T.I. Fuzzy logic-based particle swarm optimization for integrated energy management system considering battery storage degradation. *Results Eng.* **2024**, *24*, 102816. [CrossRef]
128. Guo, L.; Abdul, N.M. Design and evaluation of fuzzy adaptive particle swarm optimization based maximum power point tracking on photovoltaic system under partial shading conditions. *Front. Energy Res.* **2021**, *9*, 712175. [CrossRef]
129. Kisi, O. Modeling solar radiation of Mediterranean region in Turkey by using fuzzy genetic approach. *Energy* **2014**, *64*, 429–436. [CrossRef]
130. Erdoğdu, A.; Dayı, F.; Yıldız, F.; Yanık, A.; Ganji, F. Combining fuzzy logic and genetic algorithms to optimize cost, time and quality in modern agriculture. *Sustainability* **2025**, *17*, 2829. [CrossRef]

131. Benmouiza, K.; Tadj, M.; Cheknane, A. Classification of hourly solar radiation using fuzzy c-means algorithm for optimal stand-alone PV system sizing. *Int. J. Electr. Power Energy Syst.* **2016**, *82*, 233–241. [CrossRef]
132. Benlarbi, K.; Mokrani, L.; Nait-Said, M.S. A fuzzy global efficiency optimization of a photovoltaic water pumping system. *Sol. Energy* **2004**, *77*, 203–216. [CrossRef]
133. Guler, N.; Hazem, Z.B.; Gunes, A. Optimizing solar PV systems using fuzzy logic for Climate-Resilient Healthcare infrastructure in Kyrgyzstan. *Green Technol. Sustain.* **2025**, *3*, 100190. [CrossRef]
134. Liang, R.H.; Liao, J.H. A fuzzy-optimization approach for generation scheduling with wind and solar energy systems. *IEEE Trans. Power Syst.* **2007**, *22*, 1665–1674. [CrossRef]
135. Almaraashi, M. Short-term prediction of solar energy in Saudi Arabia using automated-design fuzzy logic systems. *PLoS ONE* **2017**, *12*, e0182429. [CrossRef]
136. de Barros Franco, D.G.; Steiner, M.T. Clustering of solar energy facilities using a hybrid fuzzy c-means algorithm initialized by metaheuristics. *J. Clean. Prod.* **2018**, *191*, 445–457. [CrossRef]
137. Memon, K.H.; Lee, D.H. Generalised fuzzy c-means clustering algorithm with local information. *IET Image Process.* **2017**, *11*, 1–12. [CrossRef]
138. Kaushik, K.P.; Hemanta, K.B. Extension of the fuzzy c means clustering algorithm to fit with the composite graph model for web document representation. *Int. J. Cogn. Res. Sci. Eng. Educ.* **2013**, *1*, 173–179.
139. Ibrahim, O.; Bakare, M.S.; Amosa, T.I.; Otuoze, A.O.; Owonikoko, W.O.; Ali, E.M.; Adesina, L.M.; Ogunbiyi, O. Development of fuzzy logic-based demand-side energy management system for hybrid energy sources. *Energy Convers. Manag. X* **2023**, *18*, 100354. [CrossRef]
140. Nur-E-Alam, M.; Abedin, T.; Samsudin, N.A.; Petrů, J.; Barnawi, A.B.; Soudagar, M.E.; Khan, T.Y.; Bashir, M.N.; Islam, M.A.; Yap, B.K.; et al. Optimization of energy management in Malaysian microgrids using fuzzy logic-based EMS scheduling controller. *Sci. Rep.* **2025**, *15*, 995. [CrossRef]
141. Subudhi, B.; Pradhan, R. A comparative study on maximum power point tracking techniques for photovoltaic power systems. *IEEE Trans. Sustain. Energy* **2012**, *4*, 89–98. [CrossRef]
142. Jiang, L.L.; Srivatsan, R.; Maskell, D.L. Computational intelligence techniques for maximum power point tracking in PV systems: A review. *Renew. Sustain. Energy Rev.* **2018**, *85*, 14–45. [CrossRef]
143. Elobaid, L.M.; Abdelsalam, A.K.; Zakzouk, E.E. Artificial neural network-based photovoltaic maximum power point tracking techniques: A survey. *IET Renew. Power Gener.* **2015**, *9*, 1043–1063. [CrossRef]
144. Ullah, K.; Wang, Y.; Zaman, A.; Imtiaz, H.H.; Ahmad, S.M.; Kumar, B. Maximum power point technique (MPPT) for PV system based on improved pert and observe (P&O) method with PI controller. *Int. Res. J. Eng. Technol. (IRJET)* **2019**, *6*, 813–819.
145. Lamnadi, M.; Trihi, M.; Bossoufi, B.; Boulezhar, A. Comparative study of IC, P&O and FLC method of MPPT algorithm for grid connected PV module. *J. Theor. Appl. Inform. Technol.* **2016**, *89*, 242–253.
146. Noman, A.M.; Addoweesh, K.E.; Mashaly, H.M. A fuzzy logic control method for MPPT of PV systems. In Proceedings of the IECON 2012-38th Annual Conference on IEEE Industrial Electronics Society, Montreal, QC, Canada, 25–28 October 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 874–880.
147. Ullah, K.; Ishaq, M.; Tchier, F.; Ahmad, H.; Ahmad, Z. Fuzzy-based maximum power point tracking (MPPT) control system for photovoltaic power generation system. *Results Eng.* **2023**, *20*, 101466. [CrossRef]
148. Faquir, S.; Yahyaouy, A.; Tairi, H.; Sabor, J. Implementing a fuzzy logic-based algorithm to predict solar and wind energies in a hybrid renewable energy system. *Int. J. Fuzzy Syst. Appl. (IJFSA)* **2015**, *4*, 10–24. [CrossRef]
149. Gellings, C.W. (Ed.) *The Smart Grid: Enabling Energy Efficiency and Demand Response*; River Publishers: New York, NY, USA, 2020.
150. Komninos, N.; Philippou, E.; Pitsillides, A. Survey in smart grid and smart home security: Issues, challenges and countermeasures. *IEEE Commun. Surv. Tutor.* **2014**, *16*, 1933–1954. [CrossRef]
151. Corchero, C.; Cruz-Zambrano, M.; Heredia, F.J. Optimal energy management for a residential microgrid including a vehicle-to-grid system. *IEEE Trans. Smart Grid* **2014**, *5*, 2163–2172.
152. Livengood, D.; Larson, R. The energy box: Locally automated optimal control of residential electricity usage. *Serv. Sci.* **2009**, *1*, 1–16. [CrossRef]
153. Jafari, M.; Malekjamshidi, Z.; Zhu, J.; Khooban, M.H. A novel predictive fuzzy logic-based energy management system for grid-connected and off-grid operation of residential smart microgrids. *IEEE J. Emerg. Sel. Top. Power Electron.* **2018**, *8*, 1391–1404. [CrossRef]
154. Chen, Y.K.; Wu, Y.C.; Song, C.C.; Chen, Y.S. Design and implementation of energy management system with fuzzy control for DC microgrid systems. *IEEE Trans. Power Electron* **2012**, *28*, 1563–1570. [CrossRef]

155. Arcos-Aviles, D.; Pascual, J.; Guinjoan, F.; Marroyo, L.; Sanchis, P.; Marietta, M.P. Low complexity energy management strategy for grid profile smoothing of a residential grid-connected microgrid using generation and demand forecasting. *Appl. Energy* **2017**, *205*, 69–84. [CrossRef]
156. Zhang, R.; VE, S.; Jackson Samuel, R.D. Fuzzy efficient energy smart home management system for renewable energy resources. *Sustainability* **2020**, *12*, 3115. [CrossRef]