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A fuzzy multi-criteria spatial decision support system for solar farm location planning

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A B S T R A C T

In recent years, investment in solar energy has increased substantially across countries. Thus, selecting convenient locations for solar farms has become a fundamental problem when determining the investment required due to differences in climatic factors, the type and availability of land, transportation infrastructures, and the quality of power lines. Multi-Criteria Evaluation approaches based on crisp data are generally used in the selection process of optimal locations. However, despite being crisp, the data available when considering the evaluation criteria of the different alternatives constitute a discrete approximation performed on a spatial grid of potential locations. Thus, we introduce a three-stage fuzzy evaluation framework designed to account for the imprecision inherent to the evaluations when identifying the most convenient location for constructing solar power farms. First, we implement ANFIS (Adaptive Neuro-Fuzzy Inference System) on the set of grid intersection crisp data points and derive a coherent set of approximations per each potential discrete location and evaluation criterion. Then, the fuzzy AHP (Analytic Hierarchy Process) method is used to determine the weights of the different criteria considered from the linguistic evaluations provided by different experts. Finally, we define a set of if-then rules combining the different ANFIS evaluation criteria and their weights within a FIS (Fuzzy Inference System) whose output is used to determine the most convenient location for constructing a solar power farm. The efficacy of the proposed evaluation framework is demonstrated through its application to the Iranian regions of Kerman and Yazd.

1. Introduction

Energy is a key element of sustainable development, economic growth and welfare [3]. Thus, the unequal distribution of oil resources in the world may result in economic and political conflicts, both now and in the future [36]. In addition, the world demand for energy is expected to increase substantially in the coming years, with oil consumption increasing from 86 million barrels per year in 2007 to a potential amount of 104 million barrels per year by 2030 [8].

Energy resources can be divided into three groups: fossil fuels, renewable and non-clean resources. While most of the world energy supply is based on fossil oil, it is widely known that fossil fuels have a significant impact on the world ecology and climate. In this regard, increasing concerns about environmental pollution have resulted in an incremental use of renewable energies through the 21st century [43]. Moreover, the reduction in their reserves has led the prices of oil and other fossil fuels to exhibit a consistently increasing trend. Therefore, most of the world countries have adopted new policies to reduce energy costs – together with the resulting pollution – [18,21,24,28]. emphasized the importance that key technologies have for the decarbonisation of the electricity sector and the gain in the efficient provision of energy.

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Renewable energies – solar, wind, biomass and geothermal – are clean resources with low environmental impacts characterized by their low costs and almost unlimited supply [49,63]. In this regard, solar energy has some advantages relative to the other types of renewable energy, which range from environmental benefits and government incentives to the availability of flexible locations [64]. Griffiths [26] presented a demand-supply model for solar energy illustrating its commercial viability in several Middle East and North Africa countries based on the improvement of relative costs and the availability of solar resources. However, collaboration between the private and the public sector is generally needed in order to overcome the budget constraints faced by poor countries and provide them with access to different renewable energy services [58].

The selection of locations for solar power plants is a complex process due to the different security, economic, environmental, and social requirements that must be considered [68]. Locations with the best solar resources cannot always be selected and several other factors play significant roles in selecting convenient locations. These factors can be categorized into economic, environmental and social classes [65]. Therefore, the use of multi-criteria decision making models becomes necessary.

Several multi-criteria evaluation methods have been used in problems involving the selection of locations. These positioning methods are described in the literature review section below. It should be emphasized that these studies generally focus on real-valued criteria whose realizations, despite being crisp, constitute a discrete approximation performed on a grid of potential locations.

That is, consider a grid mapping discretely a given set of potential locations distributed on a continuous surface. A subjective approximation must be applied by the experts when assigning values to each discrete point per evaluation criterion. At the same time, each criterion differs in relative importance and must therefore be ranked according to the subjective judgments of different experts. The approximate nature of both evaluations must be accounted for when selecting a location. In this regard, a Fuzzy Inference System (FIS) based on a sufficiently large amount of if-then inference rules can be implemented so as to smooth out the inherent imprecision and provide a coherent final evaluation.

Therefore, in order to account for the imprecision inherent to the realizations being evaluated, we introduce a three-stage fuzzy decision support framework designed to identify the most convenient location for constructing solar power farms.

a. In the first stage, a team of experts is selected to identify the main decision criteria. After retrieving the data required from different maps, ANFIS (Adaptive Neuro-Fuzzy Inference System) is implemented on the set of grid intersection points defining the regions being analyzed. ANFIS allows us to derive a coherent set of approximations per each potential discrete location and criterion.
b. Then, the fuzzy AHP (Analytic Hierarchy Process) method is used for determining the weights of the different criteria from the evaluations provided by different experts.
c. Finally, we define a set of if-then rules combining the values of the different evaluation criteria obtained from ANFIS and their weights within a FIS whose output is used to determine the most convenient location for constructing a solar power farm.

The main contribution of the current model is defined by its capacity to account for different types of imprecision while incorporating a FIS to smooth it out and provide a coherent evaluation. This is in contrast with the general approach followed by the models described in the literature review section, where ANFIS is used as a final evaluation method and fuzzy AHP is incorporated within multiple-criteria decision-making (MCDM) settings without explicitly accounting for its approximate nature.

We validate the efficacy of the proposed evaluation framework through its application to the Iranian regions of Kerman and Yazd. However, it should be noted that due to their inherent imprecision, the final evaluations obtained could differ if different experts were contacted to select and weight the criteria or different if-then rules would have been defined.

The remainder of the paper is organized as follows. Section 2 provides a short review of the related literature. Section 3 describes the ANFIS methodology, while Section 4 focuses on the FIS. Section 5 illustrates the case study and the proposed method at work. Section 6 concludes and suggests potential extensions of our model.

2. Literature review

A basic review of the positioning literature that encompasses several multi-criteria and decision support methods follows.

Farahani et al. [23] surveyed the literature on multi-criteria location problems across three main categories including bi-objective, multi-objective and multi-attribute problems. Standard MCDM techniques are commonly used in the positioning literature. For example [38], developed and tested different facility allocation models based on efficiency measures obtained from data envelopment analysis (DEA). Achillas et al. [1] proposed a decision support system for the optimal location of electrical and electronic waste treatment plants using ELimination Et Choix Traduisant la REalité (ELECTRE) III as a MCDM analysis technique. Tavana et al. [62] presented a group decision support system based on the Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) for the evaluation of alternative pipeline routes. Similarly [20], integrated a geographical information system (GIS) and the PROMETHEE IV method to locate shelters and emergency services in urban evacuation planning.

Alternatives to the standard multi-criteria location techniques can also be found in the literature. Dogan [19] proposed an integrated approach that combined Bayesian networks and the total cost of ownership to address the complexities involved in selecting an international facility for a manufacturing plant. Datta [17] designed a multi-criteria multi-facility methodology implemented in Microsoft Excel to generate scenarios for locating facilities in rural underdeveloped regions. Xu et al. [66] defined a multi-criteria location model determined by the spatial coverage of the alternatives that was used to solve the location problem of earthquake evacuation shelters.

Among the diverse methods applied, AHP has been consistently implemented as a decision support tool when performing multi-criteria spatial decision analyses [29]. In particular, AHP has been used in MCDM location models to weight the importance of the criteria considered by the corresponding GISs. Applications to positioning problems include, among many others, the planning of potential uses of land for agricultural development [5], the assessment of land capability for spatial development [2], the clearance of mine hazards [40], highway alignment [67] and the evaluation of flood hazard potentials [51].

As noted by Ref. [44]; about three quarters of the papers published on GIS multi-criteria location analysis between 1990 and 2004 focused on deterministic information. The literature has recently started to increasingly incorporate multi-criteria methods accounting for imprecision and fuzziness in GISs, since such a feature was expected to improve their analytical capacity [35]. For example [45], applied the concept of efficiency defined by DEA to location-allocation models within a fuzzy environment.

Similarly to the crisp scenarios described above, AHP has been consistently implemented in fuzzy GIS-MCDM environments [7,13]. For instance [15], defined a MCDM based on fuzzy AHP to select international tourist hotel locations, while [61] built a hybrid MCDM method based on fuzzy AHP that considered tangible and intangible factors in the selection of optimal locations. Fuzzy AHP has prevailed as a commonly used methodology despite the initial criticism received regarding the ambiguity of the questions formulated and their lack of reference to the scales employed to measure the different criteria [25].

Indeed, fuzzy approaches can provide better approximations than crisp ones when evaluating the suitability of potential location alternatives. Montgomery and Dragićević [46] noted that crisp GIS-based multi-criteria evaluation methods may not be able to fully capture the whole range of human reasoning and suggested improved soft computing evaluation methods that exhibited an improved performance.

Thus, given the linguistic evaluations received from the experts in the current model, we will apply fuzzy AHP together with the extent analysis method to derive the relative weights assigned to the different decision criteria considered. We focus now on the specific problem of positioning when dealing with the construction of solar power plants.

2.1. Solar farm positioning

An extensive review of the literature on decision support methods applied to renewable energy investments is provided by Ref. [59]; while [60] review the recent literature on fuzzy decision making in renewable energy systems.

The literature on solar farm positioning is characterized by the use of crisp GISs to evaluate the different criteria determining the relative optimality of a given set of potential locations. For example [9], used a GIS to investigate the energy production capacity of power plants in Spain and their optimal location. Similarly [34], suggested convenient locations for solar farms in Colorado using GIS modeling techniques. Dagdougui et al. [16] defined a GIS-based decision making model to select convenient locations for constructing renewable hydrogen production systems. Pavlović et al. [50] selected the most convenient among 23 potential locations in Serbia using the efficacy of silicon solar cells and data on solar irradiation. Besarati et al. [6] programmed a 5 MW solar power plant for 50 alternative locations in Iran based on their power generation, capacity factors, and annual greenhouse gas emissions. Sánchez et al. [57] implemented a GIS-MCDM model that used AHP to calculate the weights of the criteria and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to evaluate the alternatives. Uyan [64] also incorporated AHP within a GIS in order to select solar farm sites in Turkey.

Several other models implementing a variety of alternative MCDM positioning techniques have also been defined in the literature. For example [4], applied a MCDM method to select an optimal project for the construction of solar power plants in Burkina Faso. Nguyen & Pearce [47] designed an algorithm that classifies each region of the world in terms of its capacity to develop solar farms. In this regard [27], proposed a model to overcome the alternations encountered in different time zones. Their method considered optimal placements across broad geographical areas as well as the size and ratio of production and saving capacity of each place.

Suganthi et al. [60] highlighted the fact that fuzzy MCDM techniques are generally considered to be complex due to their computational requirements and therefore focus on model testing through numerical analysis and simulation. Among the contributions to the literature, we emphasize the following ones. Salah et al. [56] defined a fuzzy algorithm that decided whether the connection of domestic appliances in the north of Tunisia was made to the electrical grid or a photovoltaic panel. Charabi and Gastil [10] presented a geographical survey model based on fuzzy quantifiers for positioning photovoltaic technologies in Oman. Ouammi et al. [48] used artificial neural networks to predict monthly and annual solar irradiance so as to identify the most convenient locations for constructing solar power plants in Morocco.

Given the potential advantages described in the previous section, fuzzy decision support methods have been increasingly implemented when evaluating renewable energy systems. In this regard, fuzzy AHP remains as one of the most common methods applied [60], though not particularly when considering solar farm positioning problems [42].

Finally Suganthi et al. [60], emphasized the substantial amount of research on neuro-fuzzy and ANFIS models developed in recent years and used extensively in solar photovoltaic control/smart grid systems [12,37,41]. In these cases, ANFIS is neither included within a more complex MCDM environment nor its approximate nature accounted for when delivering the final evaluations. In the current paper, we consider the uncertainty inherent to the ANFIS modeling technique and implement a FIS based on 37 if-then inference rules to generate a more reliable set of results.

3. ANFIS

Fuzzy systems are based on if-then rules that cannot be analyzed using classical probability theories. In this regard, the aim of fuzzy logic is to extract accurate results using a set of rules defined by specialists. At the same time, neural networks are capable of learning using the observed data and determine the network parameters so that per each selected input a given output can be obtained. However, and like fuzzy systems, neural networks cannot deduce using linguistic expressions and require crisp values to provide the required output [32].

As a result, the Adaptive Neuro-Fuzzy Inference Systems known as ANFIS was introduced by Ref. [32] in order to improve the learning capability of neural networks, obtain more accurate approximations and rely on a simpler structure. ANFIS combines the learning capabilities of neural networks and the adaptive properties of fuzzy inference systems. In particular, ANFIS is a multilayer neural network with the capacity to find every kind of nonlinear mapping or model that can accurately relate inputs (primary values) to outputs (predicted values). Its structure is described in Fig. 1.

In this structure, input and output nodes refer to inputted and predicted values, respectively. In order to simplify the description, a two-input single-output network is considered. As can be seen in Fig. 1, ANFIS is a 5-layered network where each layer has different nodes and each node is located within a fixed or an adaptive layer. The different layers and their corresponding nodes are described below.

First layer: each node in this layer delivers a membership value assigned to each of the non-fuzzy input variables of the model, x and y, which are introduced in Layer zero. Output values are determined based on the degree of membership of the inputs to the fuzzy sets A_i and B_i, with $i = 1,\ 2$. More precisely, A_1 and A_2 represent fuzzy linguistic labels applied to input x, while B_1 and B_2 are associated with input y. Each one of the four nodes defining this layer delivers a membership function associated with the different linguistic labels that define the node.

That is, node i delivers the output $O^x_{1,i}$ for the input x in the layer

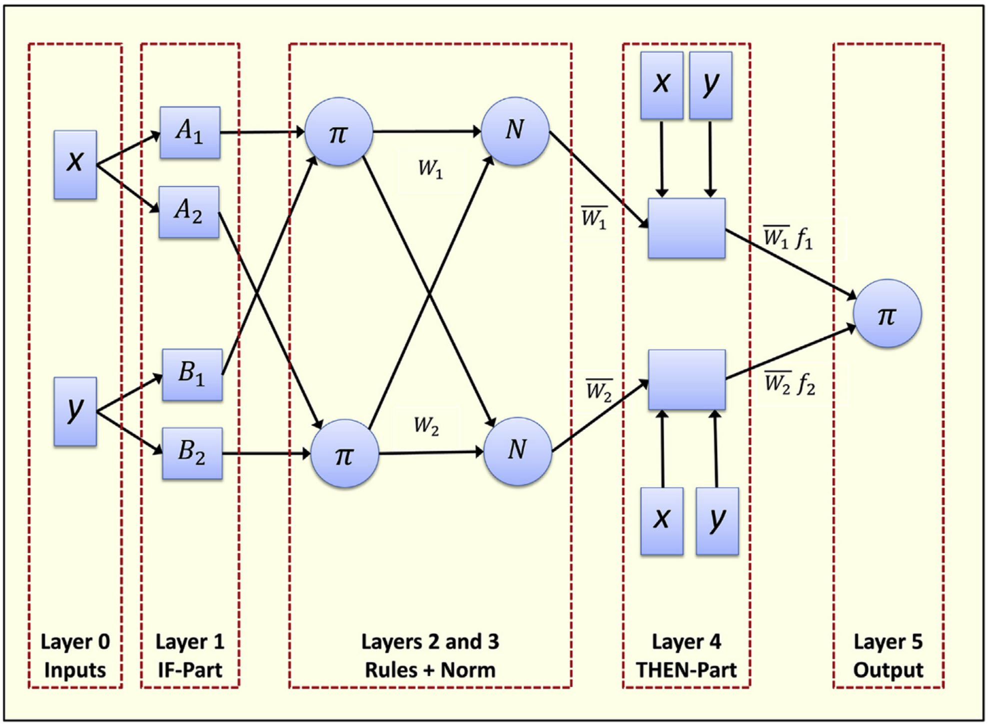

Fig. 1. ANFIS structure.

1:

$$O^x_{1,i} = \mu_{A_i}(x), \quad i = 1,2 \tag{1}$$

and the output of node i for the input y, $O^y_{1,i}$, is given by:

$$O^y_{1,i} = \mu_{B_i}(y), \quad i = 1,2 \tag{2}$$

where μ_{A_i} and μ_{B_i} are the membership functions of A_i and B_i, respectively.

Real-life systems with engineering applications deal with crisp numerical variables, implying that in order to use a fuzzy system a mapping between the crisp inputs of the system and a fuzzy set should be created. To do so, ANFIS generally applies Gaussian fuzzifiers within its first layer.

Second layer: this layer is composed by nodes of rules, with each node calculating the participation degree of a rule. $O_{2,i}$ defines the output of the $ith-$node in the second layer, which equals the product of the degrees of membership obtained in the first layer for each input:

$$O_{2,i} = w_i = \mu_{A_i}(x)\, \mu_{B_i}(y), \quad i = 1,2 \tag{3}$$

Third layer: this layer includes normalized nodes that calculate the ratio of the participation degree of each rule to the sum of the participation degrees of all rules. As a result, the output obtained from this layer is defined as:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{4}$$

Fourth layer: this layer consists of adaptive nodes endowed with a node function f_i. The output of each node is given by:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i), \quad i = 1,2 \tag{5}$$

where $\overline{w}_i$ is the output obtained from the $ith-$node in the previous layer and r_i, q_i, and p_i are linear consequent parameters.

Fifth layer: the node composing this layer defines the value of the overall ANFIS output as the sum of the outputs obtained from the nodes of the previous layer:

$$O_{5,i} = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{\sum_{i=1}^{2} w_i} \tag{6}$$

The ANFIS network applies a hybrid learning algorithm that includes the gradient descent algorithm and the recursive least squares method. The gradient descent algorithm is used for updating the nonlinear parameters of the network while estimating the recursive least squares is used for regulating the weights of the network [30]. The training error of the network is defined by Equation (7):

$$E = \sum_{i=1}^{2} \left(f_i - \overline{f}_i\right)^2 \tag{7}$$

where f_i and $\overline{f}_i$ are the desired and estimated outputs of the network per $ith-$input, respectively.

In the current paper, we have used ANFIS to estimate the f_i functions related to each of the five decision criteria analyzed. This was done by inputting 300 points of the investigated space in such a way that a continuous approximation covering the whole space could be obtained. Those points that were deemed to be appropriate in terms of a criterion were assigned a value of one, while those points considered to be inappropriate were assigned a value of zero. Accordingly, other points were assigned priority values between 0 and 1. These values were used by ANFIS to estimate the corresponding set of f_i functions.

That is, the different location alternatives have been mapped from their respective geographic locations to the coordinate system used by ANFIS to provide a continuous approximation. In particular, each discrete point defining the inputted grid provides an evaluation of each geographic location per decision criterion. It should be noted that these values constitute a discrete and subjective approximation defined by the experts evaluating the locations. However, the priority function generated by ANFIS for the different location alternatives is a continuous surface map – where each point represents a geographical location –. A priority function is generated for each criterion and used to evaluate the relative optimality of each location alternative. The best alternative will therefore be described in a final grid representing the space of potential locations, which can be mapped back to the set of geographic locations in a map.

4. Fuzzy inference system design

Approximate inference is the extraction of inaccurate results based on inaccurate hypotheses. In this regard, the calculation and measurement processes implemented by experts are generally more consistent with fuzzy calculations and approximate inference than with accurate mathematical calculations and conventional logics.

Fuzzy inference is the process of designing mappings that lead from an input to an output value using fuzzy logic. The process of fuzzy inference requires using all the following tools and concepts:

1. Membership function
2. Operators of fuzzy logic
3. If-then rules

The main objective of these systems is to model the knowledge of an expert about complicated issues by providing a solid foundation for a formal inference theory based on verbal variables and knowledge. The basis of this theory is the representation of propositions in the form of expressions that attribute fuzzy sets as values to variables.

FISs have been successfully applied in several research areas such as automatic control, data classification, and the analysis of decisions in expert systems. In this regard, FISs provide the analytical tools required to apply approximate reasoning in the current decision framework so as to identify and select the best potential locations.

4.1. If-then rules

Fuzzy sets and fuzzy operators are used in the formulation of fuzzy if-then rules such as:

If x is equal to a, then y is equal to b,

where (a) and (b) are verbal values defined by fuzzy sets on the reference ranges X and Y, respectively. The “if” part of the rule (x is equal to a) is known as the premise or input, while the “then” part (y is equal to b) is called the conclusion or output.

The inputs of a fuzzy if-then rule are generally real values while their outputs are fuzzy sets that must be defuzzified so as to assign a crisp value to the output variable. That is, the results obtained from each rule are determined by the fuzzy set assigned to the output variables. In this regard, the results are defined in such a way that if an input is true with a particular degree of membership, then the output is true with the same degree of membership. Consequently, the inference fuzzy set function applied modifies the output variable based on the degree of membership of the inputs. We will apply the truncation method included in the fuzzy logic toolbox of MATLAB to modify the output fuzzy set.

The implementation of fuzzy if-then rules requires following a specific three-stage process consisting of:

4.1.1. Stage 1: Fuzzification of inputs

The real values of each input variable and the membership functions defined are used to fuzzify the inputs and transform them into membership degree values between zero and one. If a rule has only one input, the input membership degree is the degree of support of the rule.

4.1.2. Stage 2: Applying fuzzy operators in rules with multiple inputs

If a rule has multiple inputs, the use of fuzzy operators such as “or” and “and” can be used to merge the degree of membership of all inputs into a numerical value between zero and one. This value indicates the degree of support of the rule.

4.1.3. Stage 3: Applying the inference method to deduce and determine output values

The degree of support of all rules is used for identifying the output fuzzy sets. The result obtained from a fuzzy rule is the assignment of a fuzzy set to each output variable. This fuzzy set is represented using a membership function selected for determining the quality of the outputs. If inputs are true to some extent (i.e. their degree of membership is less than one), then the output reference collection is modified according to the inference method applied.

Note that, an if-then rule is not generally significant on its own. In a fuzzy inference system, two or several rules that can be contrasted are generally required. The outputs of each rule can then be integrated to construct a single output fuzzy set that has to be defuzzified so as to obtain a single final value.

5. Proposed method

In the current study, we start by defining the geographic location problem at hand and selecting the evaluation criteria that will be used to determine the most convenient location for constructing a solar power farm. These criteria have been selected by consulting several experts and reviewing the related literature. Then, given the discrete set of points selected from the regions of analysis and their assigned priorities (defined between 0 and 1), ANFIS is applied to obtain continuous estimated functions per each decision criterion. After estimating these functions, and given the existing independence between criteria, the fuzzy AHP technique is used to determine the relative weight of each criterion. Finally, the values obtained for each alternative per criterion are weighted and incorporated into a FIS that, after applying 37 if-then inference rules, assigns a final value to each point in the two-dimensional decision space.

The proposed three-phase method is depicted in Fig. 2. The first phase is intended to define the problem, establish a team of experts and identify the relevant criteria for solar power plant positioning. The second phase is designed to determine the weights of the criteria using the fuzzy AHP method. The third phase is used to extract fuzzy if-then rules and to select the most suitable location.

5.1. Phase 1: Defining and estimating criteria

After defining the location problem, reviewing the relevant literature and considering the suggestions of several experts, the criteria described in Table 1 have been chosen to select convenient locations for constructing a solar power farm in the Iranian regions of Kerman and Yazd.

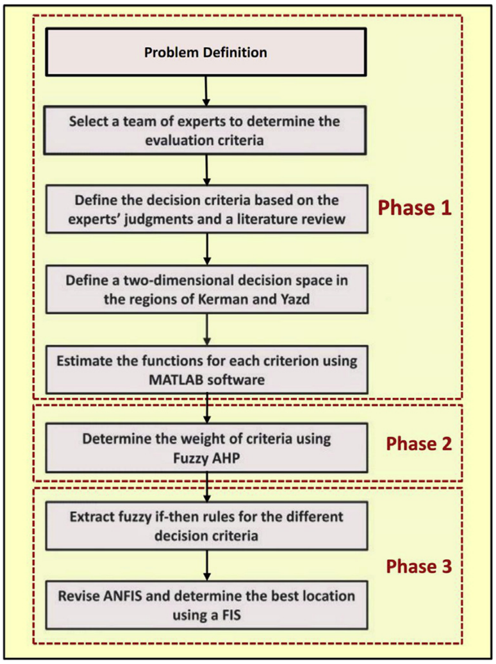

Fig. 2. Proposed framework.

Table 1
Criteria considered for selecting the most suitable solar power plant location according to the literature review.

Field of evaluation	Criteria	Priority	Resource (authors)
Environmental criteria	Distance from residential areas	Max	[68]
	Access to land	Max	[48]
	Intensity of solar radiation	Max	[71]
Economic criteria	Distance from roads	Min	[68]
	Distance from transmission power lines	Min	[68]

We describe these criteria in more detail through the following sections.

5.1.1. Environmental criteria

Distance from residential areas: constructing a solar power plant near urban or rural areas can have negative environmental effects on urban and population development. Therefore, a convenient location for solar farms should be at least 500 m away from residential areas [68].

In the current study, we identify the urban and rural areas of Kerman and Yazd using information retrieved from Google maps. The areas located far from cities and villages were assigned a priority of one, while other areas were assigned priorities lower than one based on their closeness to cities and villages. Then, these priority values were used to evaluate a set of two-dimensional points covering the whole area occupied by both regions. These values were entered in MATLAB, whose ANFIS toolbox delivered an estimated priority function for the distance criterion.

As already stated, the three dimensional priority function generated by ANFIS for the different location alternatives is a continuous surface map where each point corresponds to a geographical location. That is, the discrete input values defined on the x and y axes represent the coordinates of the geographic locations on the corresponding maps, while the z axis represents the score value assigned to each coordinate based on each decision criteria and ranges within the [0, 1] interval. The map of the areas analyzed in terms of the distance criterion, together with its corresponding legend, and the resulting estimated priority function are illustrated in Fig. 3(a).

Intensity of solar radiation: this is one of the most significant environmental factors to consider [71]. The data required was retrieved from the maps available at the Iranian site of new energies (http://www.suna.org.irby/en/home). As was done with the previous criterion, two-dimensional points along with their priorities were entered in MATLAB, whose ANFIS toolbox delivered an estimated priority function for the solar radiation criterion. The corresponding map together with its legend and the resulting estimated priority function are illustrated in Fig. 3(b).

Access to land: the availability of accessible land is a key factor for the investment on energy [31]. In particular, the existence of accessible land is one of the environmental factors used to select convenient locations for constructing solar power plants [48]. Consider the geographical map of the rugged and mountainous regions of Yazd and Kerman presented in Fig. 3(c).[1] We have assigned a priority value of one to the areas with higher levels of access to unused land, while other areas with less accessibility have been assigned a priority lower than one. The resulting estimated priority function is also illustrated in Fig. 3(c).

5.1.2. Economic criteria

Distance from roads: nearness to main roads can effectively reduce the costs of constructing solar power plants. Consequently, those locations closer to main roads should be assigned a higher priority (Yuan, 2013). The map of roads in the studied area has been retrieved from the Iranian Ministry of Roads and Urban Development (http://www.141.ir/SitePages/Index.aspx) and is presented in Fig. 4(a) together with the corresponding estimated priority function.

Distance from transmission power lines: nearness to transmission power lines is economically important (Yuan, 2013). Therefore, those areas located near transmission power lines must be assigned higher priority values. The map of transmission power lines (that has been retrieved from http://amar.tavanir.org.ir) is illustrated in Fig. 4(b) together with the estimated priority function obtained from the ANFIS toolbox.

5.2. Phase 2: Fuzzy AHP with extent analysis

The uncertainty about referral judgments increases the uncertainty faced when prioritizing alternatives and consequently, it makes the determination of agreement difficult. Among the main methods developed to deal with hierarchical decisions under ambiguity in the positioning literature, we will consider the fuzzy AHP one [39]. A discussion about its potential imprecision and the alternative ranking methods available in the literature will be provided in Section 6.

In the current setting, verbal variables are transformed into triangular fuzzy numbers of the form M_i^j, with $i = 1, \ldots, n$ referring to the row of the paired comparison matrix and $j = 1, \ldots, m$ to the column. A summary of the main steps applied to solve fuzzy AHP models using the extent analysis method follows. A more detailed description can be found in Refs. [11] and [70].

[1] The map can be retrieved from the following link: https://upload.wikimedia.org/wikipedia/commons/thumb/3/31/Iran_relief_location_map.jpg/672px-Iran_relief_location_map.jpg.

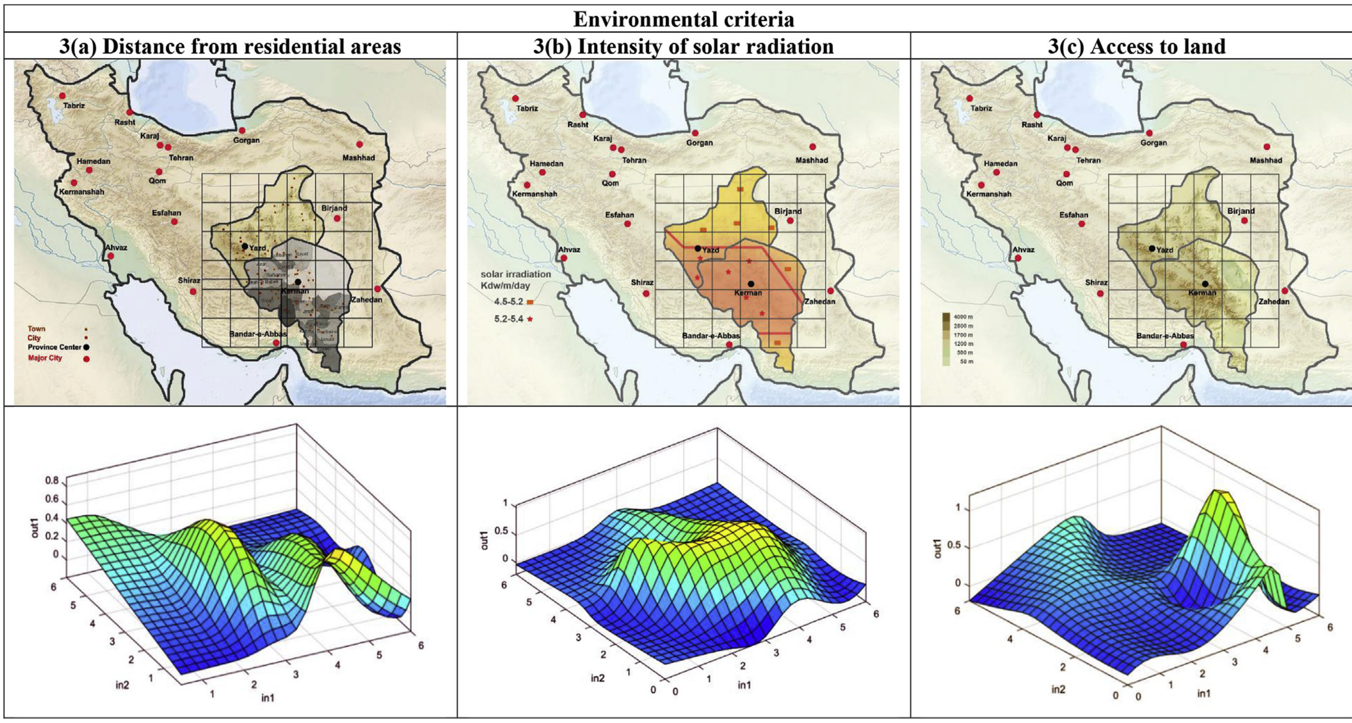

Fig. 3. Maps and ANFIS estimated function for the different environmental criteria.

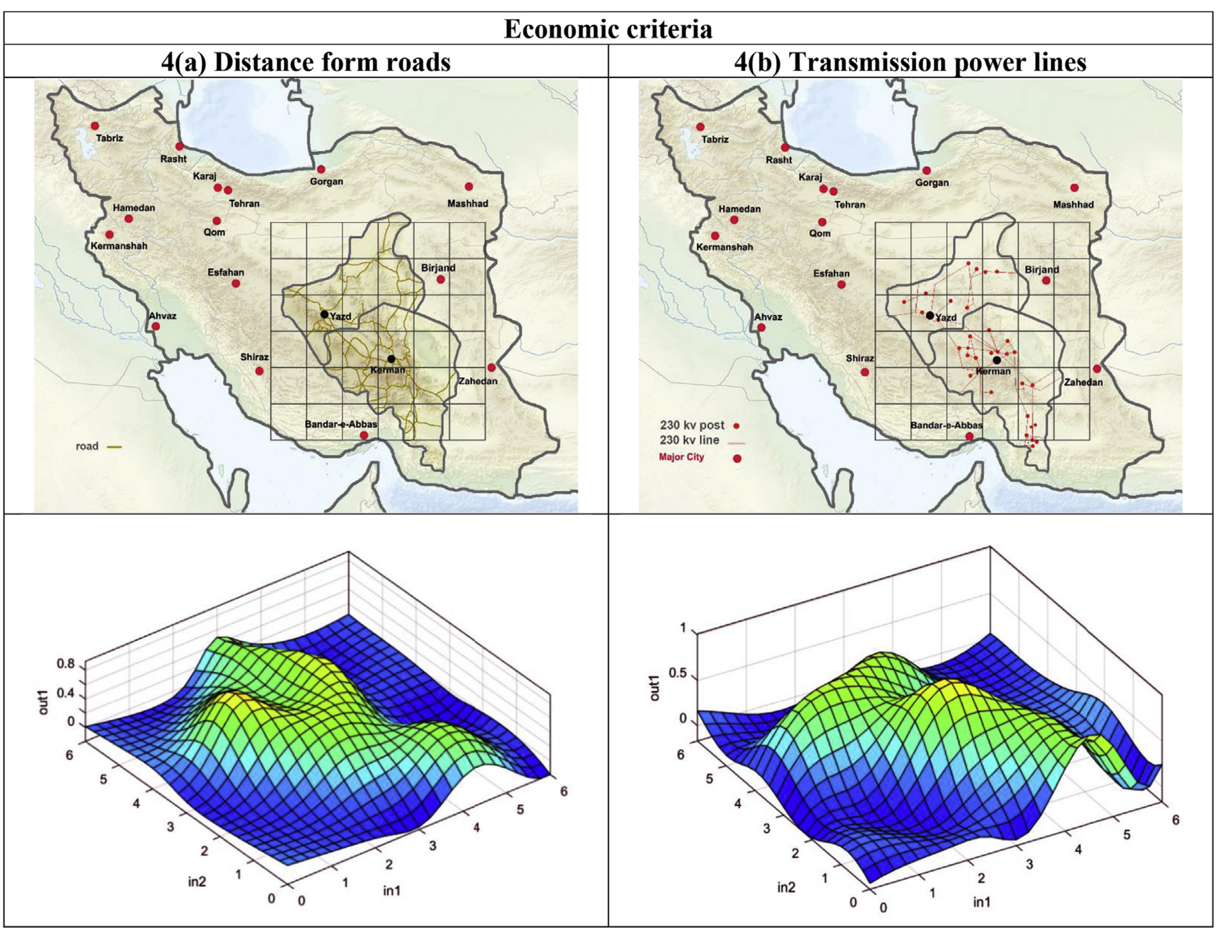

Fig. 4. Maps and ANFIS estimated function for the different economic criteria.

1. The value S_i of the fuzzy synthetic extent is calculated for each of the i rows composing the paired comparison matrix

$$Si = \sum_{j=1}^{m} M_i^j \cdot \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_i^j \right]^{-1} \tag{8}$$

where

$$\sum_{j=1}^{m} M_i^j = \left(\sum_{j=1}^{m} u_{ij}; \sum_{j=1}^{m} m_{ij}; \sum_{j=1}^{m} l_{ij} \right) \tag{9}$$

2. The magnitude degree of the S_i triangular fuzzy numbers is calculated through pairwise comparisons as follows

$$\begin{cases} M_1 > M_2 & v(S1 > S2) = 1 \\ M_1 \leq M_2 & v(S2 \geq S1) = hgt(S1 \cap S2) = \dfrac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} \end{cases} \tag{10}$$

with

$$v(S1 > S2) = \sup_{x>y} \left[\min\left(\mu_{M_1}(x), \mu_{M_2}(y) \right) \right] \tag{11}$$

where $\mu_{M_1}(x)$ refers to the membership function associated to the fuzzy number M_1.

3. Assume now that

$$d(Ai) = \min v(Si > Sk), \quad \text{for} \; k = 1, \ldots, n \text{ with } k \neq i \tag{12}$$

then, the weight vector W can be defined as follows

$$W = (d(A1), d(A2), \ldots, d(An))^T \tag{13}$$

and normalized, such that

$$W' = \left(d(A1) \Big/ \sum_{i=1}^{n} d(Ai), d(A2) \Big/ \sum_{i=1}^{n} d(Ai), \ldots, d(An) \Big/ \sum_{i=1}^{n} d(Ai) \right)^T \tag{14}$$

where W' is a crisp number.

4. Steps 1–3 are repeated for all paired comparison matrices in order to obtain the corresponding normalized weight vectors.
5. The hierarchical structure is drawn using the weights obtained and calculated via the AHP method.

Table 2 presents the fuzzy paired comparison matrix obtained from the evaluations of the experts consulted, while Table 3 describes the normalized weights assigned to each criterion after implementing the extent analysis method. These weights will be applied when defining the if-then rules in the next phase of the evaluation process, which is described in the following section.

5.3. Phase 3: Defining the FIS based on if-then rules

In the final phase, we design the fuzzy inference system – including inputs, fuzzy rules and outputs – through the following four steps:

1. The first step to construct the FIS consists of fuzzifying the variables. The input (values of decision criteria) and output variables are both transformed into verbal variables (low, moderate, high). An overview of the FIS is presented in Fig. 5.

The number of input and output variables is also defined in this section. The five decision criteria considered (distance from residential areas, intensity of solar radiation, access to land, distance from roads, and distance from transmission power lines) are denoted by M1, M2, M3, M4, and M5, respectively, while the output variable is identified as OUT.

2. The triangular membership functions associated to the (low, moderate, and high) input and output variables are defined next. Fig. 6 illustrates the functions considered for the "distance from residential areas" criterion. Note that the domain on which the functions are defined is $[0, 1]$, coinciding with that of the output obtained from ANFIS. The membership functions of the other inputs and the output variable – which is described in Fig. 7 – are defined in the same way.
3. Given the information about inputs and outputs provided in the previous steps, we define 37 if-then inference rules, all of which are presented in Table 4. Note that a total of 3^5 rules could have been defined. However, such a large number would complicate the analysis considerably without adding any particular insight. Thus, the experts evaluating the weights of the different criteria were also consulted so as to select the more plausible combinations, which led to the 37 rules considered.

It should be noted that MATLAB's Fuzzy Logic Toolbox does not

Table 3
Criteria and normalized weights.

Criteria	Weight	Normalized weight
Distance from residential areas	0.58	0.185
Intensity of solar radiation	1.00	0.315
Access to land	0.97	0.309
Distance from roads	0.25	0.080
Distance from transmission power lines	0.36	0.110

Table 2
Fuzzy paired comparison matrix.

Criteria	Distance from residential areas	Solar radiation intensity	Access to land	Distance from roads	Distance from transmission power lines
Distance from residential areas	(1,1,1)	(1,1.2, 1.5)	(0.2, 0.4, 0.45)	(1.5, 1.7, 2)	(0.8, 0.9, 1)
Solar radiation intensity	(0.67, 0.83, 1)	(1,1,1)	(1, 1.5, 2)	(1.5, 1.7, 2)	(2, 2.5, 3)
Access to land	(2.2., 2.5, 5)	(0.5, 0.66, 1)	(1,1,1)	(1, 1.5, 2)	(1., 1.2, 1.5)
Distance from roads	(0.5, 0.58, 0.66)	(0.5, 0.83, 1)	(0.5, 0.66, 1)	(1, 1, 1)	(0.8, 0.9, 1)
Distance from transmission power lines	(1, 1.1, 1.25)	(0.33, 0.4, 0.5)	(0.66, 0.83, 1)	(1., 1.1, 1.25)	(1,1,1)

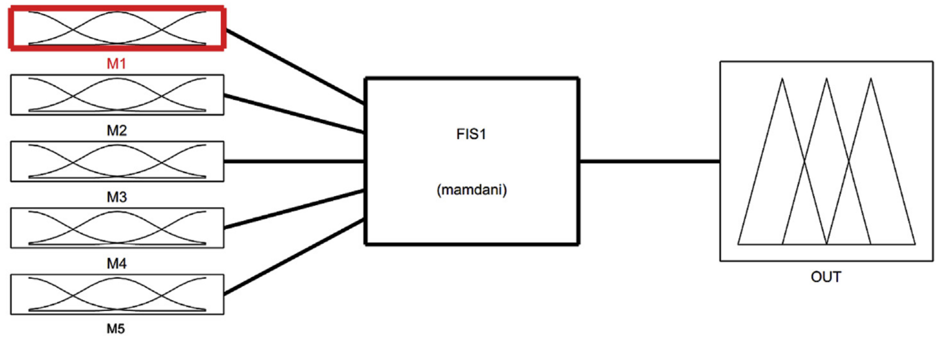

Fig. 5. FIS overview.

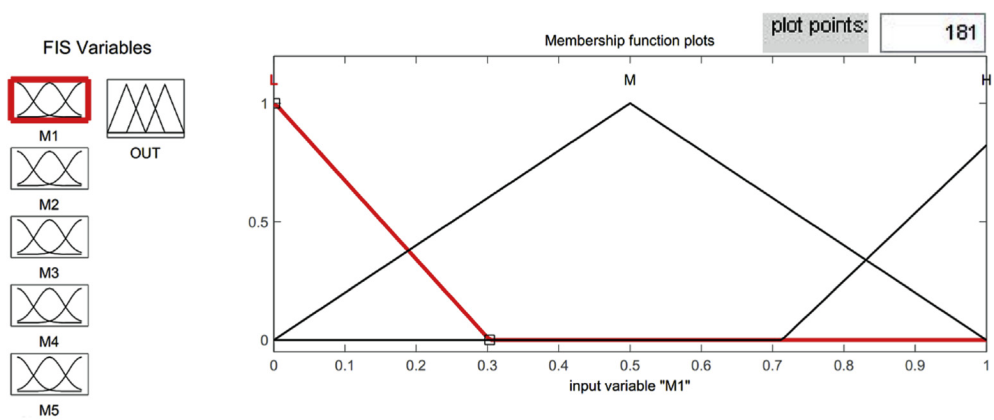

Fig. 6. Verbal variables and their membership functions related to the five criteria.

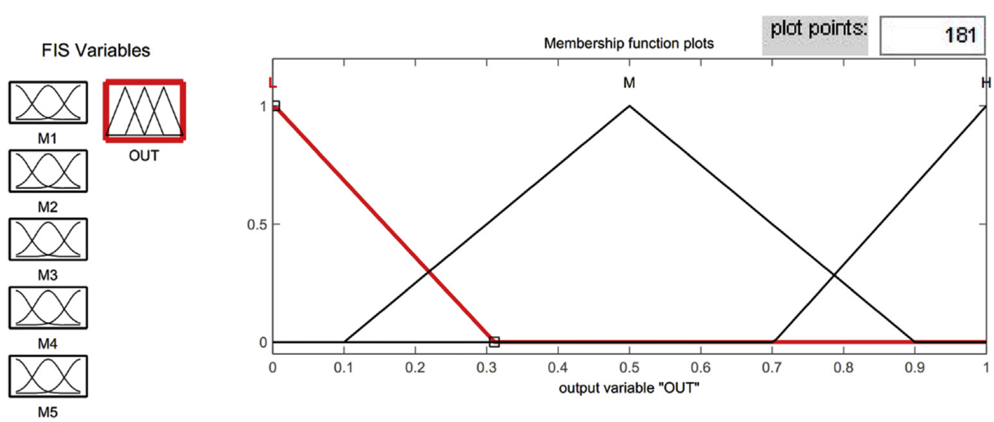

Fig. 7. Membership functions related to outputs.

allow for the weights of the different criteria to be directly implemented in the analysis. Thus, the weights have been incorporated when defining the if -then rules in such a way that if a criterion has a higher weight than others, then it should have a higher impact on the evaluation output. For example, consider the following rule: If M1 is M and M2 is L and M3 is L and M4 is H, and M5 is M. Given the weights obtained for the different decision criteria and described in Table 3, 0.624% of the rule belongs to the L part of the fuzzy membership function, 0.295% to the M part and only 0.08% belongs to the H part. Thus, an output value of L should be assigned to the rule. However, if we were to assume the same weight on all the criteria, then the above rule would have been assigned an output value of M.

4. After defining the set of if-then rules, the FIS can be finally implemented. The system is described in Fig. 8, where rows represent the fuzzy if-then rules, while columns refer to the different inputs and the output variable. It should be noted that the M1 to M5 (and OUT) column values observed in this figure do not correspond to the criteria weights being applied but to a sensitivity analysis tool for the FIS network, whose values do not modify the results obtained.

After developing the if-then rules and designing the

Table 4
Extracted rules for determining the most suitable solar power plant location.

Number	If-then rules
1	If M1 is H and M2 is H and M3 is H and M4 is H, and M5 is H, then OUT is H
2	If M1 is H and M2 is H and M3 is H and M4 is H, and M5 is M, then OUT is H
3	If M1 is H and M2 is H and M3 is H and M4 is M, and M5 is H, then OUT is H
4	If M1 is H and M2 is H and M3 is M and M4 is H, and M5 is H, then OUT is H
5	If M1 is H and M2 is M and M3 is H and M4 is H, and M5 is H, then OUT is H
6	If M1 is H and M2 is M and M3 is M and M4 is M, and M5 is H, then OUT is M
7	If M1 is M and M2 is H and M3 is H and M4 is H, and M5 is H, then OUT is H
8	If M1 is M and M2 is L and M3 is H and M4 is H, and M5 is H, then OUT is H
9	If M1 is H and M2 is M and M3 is H and M4 is H, and M5 is M, then OUT is H
10	If M1 is H and M2 is H and M3 is H and M4 is M and M5 is M, then OUT is H
11	If M1 is H and M2 is H and M3 is M and M4 is M, and M5 is M, then OUT is H
12	If M1 is H and M2 is H and M3 is H and M4 is M, and M5 is L, then OUT is H
13	If M1 is H and M2 is H and M3 is H and M4 is L, and M5 is L, then OUT is H
14	If M1 is M and M2 is M and M3 is H and M4 is H, and M5 is H, then OUT is M
15	If M1 is M and M2 is L and M3 is L and M4 is H, and M5 is H, then OUT is L
16	If M1 is L and M2 is H and M3 is H and M4 is L, and M5 is L, then OUT is M
17	If M1 is L and M2 is L and M3 is H and M4 is H, and M5 is L, then OUT is L
18	If M1 is L and M2 is M and M3 is L and M4 is M, and M5 is L, then OUT is L
19	If M1 is H and M2 is H and M3 is H and M4 is H, and M5 is M, then OUT is H
20	If M1 is L and M2 is H and M3 is H and M4 is H, and M5 is H, then OUT is M
21	If M1 is L and M2 is L and M3 is M and M4 is H, and M5 is H, then OUT is L
22	If M1 is M and M2 is M and M3 is L and M4 is L, and M5 is L, then OUT is M
23	If M1 is M and M2 is M and M3 is M and M4 is M, and M5 is M, then OUT is M
24	If M1 is H and M2 is H and M3 is L and M4 is L, and M5 is L, then OUT is H
25	If M1 is L and M2 is L and M3 is L and M4 is L, and M5 is L, then OUT is L
26	If M1 is H and M2 is M and M3 is M and M4 is M, and M5 is M, then OUT is M
27	If M1 is M and M2 is L and M3 is M and M4 is H, and M5 is H, then OUT is M
28	If M1 is M and M2 is L and M3 is H and M4 is M, and M5 is M, then OUT is M
29	If M1 is H and M2 is L and M3 is L and M4 is H, and M5 is H, then OUT is L
30	If M1 is H and M2 is L and M3 is H and M4 is L, and M5 is H, then OUT is H
31	If M1 is L and M2 is M and M3 is L and M4 is M, and M5 is L, then OUT is L
32	If M1 is H and M2 is L and M3 is L and M4 is L, and M5 is L, then OUT is L
33	If M1 is L and M2 is L and M3 is L and M4 is H, and M5 is L, then OUT is L
34	If M1 is L and M2 is H and M3 is L and M4 is L, and M5 is M, then OUT is L
35	If M1 is M and M2 is L and M3 is L and M4 is L, and M5 is H, then OUT is L
36	If M1 is L and M2 is H and M3 is M and M4 is H, and M5 is H, then OUT is H
37	If M1 is L and M2 is M and M3 is M and M4 is H, and M5 is H, then OUT is M

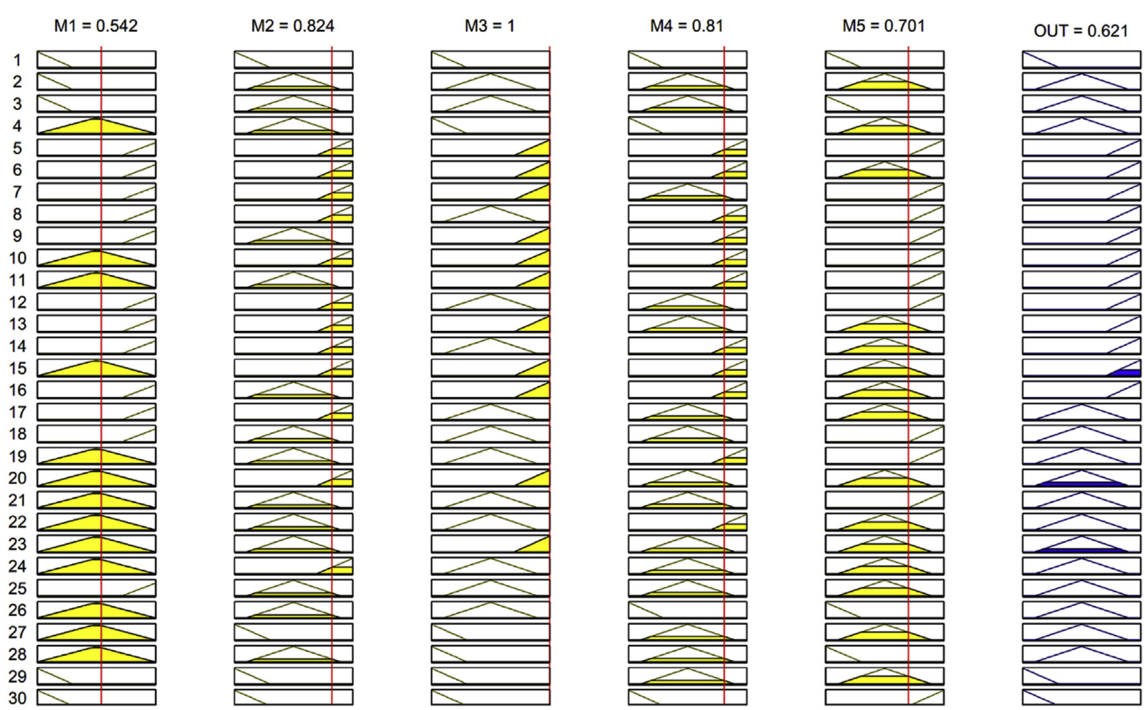

Fig. 8. Fuzzy inference system.

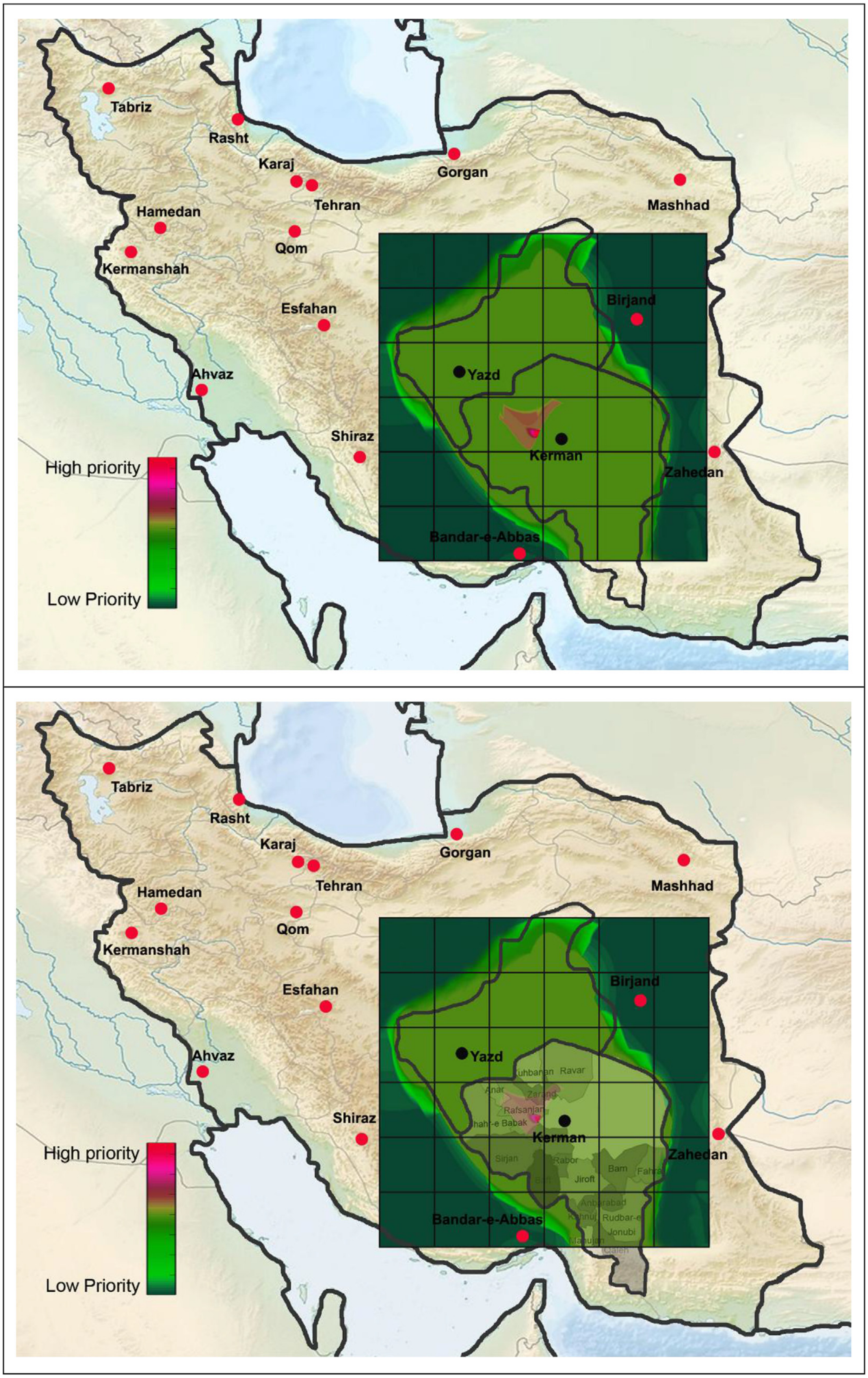

Fig. 9. Final output maps.

corresponding FIS, output values were obtained for each point defining the area investigated from the Kerman and Yazd regions. Among the output locations, the most convenient one was given by the point (2.84, 2.36) with a priority of 0.566 based on the five criteria considered. This location corresponds to Rafsanjan City and has been identified in Fig. 9, which provides two output maps describing the priorities assigned to the different solar power farm locations with different levels of detail. The upper map focuses on the output obtained from the FIS while the lower one provides a more detailed description of the counties forming the Kerman province and neighboring the selected location.

6. Discussion, conclusion and future research directions

The selection of locations for solar power plants is a complex process due to the different security, economic, environmental, and social requirements that must be considered. Locations with the highest solar resources cannot always be selected and several other factors play significant roles in selecting convenient locations. Therefore, the use of MCDM models becomes necessary.

We have defined a three-stage fuzzy evaluation framework designed to identify the most convenient location for constructing solar power farms. This framework combines three different fuzzy decision techniques, namely, ANFIS, fuzzy AHP and FISs. The main advantage of this type of approach is that it allows us to account for the imprecisions inherent to the evaluations of the different locations provided by the experts. That is, despite being crisp, the data generally available when considering the evaluation criteria of the different alternatives constitute a discrete approximation performed on a grid of prospective locations.

In this regard, the main contribution of our model could be considered its capacity to account for the imprecision inherent to the ANFIS and fuzzy AHP evaluations by incorporating a FIS so as to smooth it out and provide a coherent output set. This approach contrasts with the standard ones applied in the fuzzy decision making literature on positioning, where ANFIS and fuzzy AHP are used to provide final evaluations within MCDM settings without explicitly accounting for their approximate nature. As already noted, the imprecision inherent to the evaluations implies that the final results obtained could differ if the group of experts contacted to select and weight the criteria were modified or different if-then rules defined.

The approximate nature of the numerical evaluations provided by the experts when comparing alternatives within the AHP has already been emphasized by Refs. [52] and [53]. These authors noted that the use of fuzzy set theoretical elements within an already approximate setting such as that of AHP could increase the imprecision of the analysis performed and distort the results obtained. This effect is partly due to the uncertainties associated with the numerical representation of the judgments provided by the decision makers. Moreover [14], highlighted the fact that the sensitivity of the criteria weights obtained from pairwise comparisons to input and output modifications contributes to the uncertainties inherent to AHP-based spatial MCDM processes. Therefore, the use of a FIS aimed at smoothing out the imprecision inherent to the fuzzy AHP-based decision process should help providing a more coherent output set when evaluating renewable energy systems.

Finally, besides AHP, the main standard MCDM methods employed in the positioning literature consist of TOPSIS and the Elimination and Choice Expressing Reality (ELECTRE) and PROMETHEE families. As stated by Ref. [54]; these methods provide an elegant and powerful framework of analysis when dealing with linear decision problems but are subject to rank reversal phenomena when considering nonlinear problems. That is, the addition or removal of a given subset of alternatives could modify the resulting rankings obtained. The evaluation process may therefore require a rank reversal free approach such as the Characteristic Objects Method (COMET) [22,55] in order to obtain a consistent set of weights for the different decision criteria.

With this last remark in mind, we suggest that potential extensions of the current decision environment should incorporate additional decision criteria and consider alternative weighting methods, other than fuzzy AHP, while adapting the different if-then rules that define the FIS. Moreover, the selection of locations to construct power plants exploiting other types of energy resources, such as wind, is also suggested.

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