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An integrated fuzzy AHP- fuzzy DEA approach for location optimization of renewable energy plants

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Abstract

This study presents an integrated approach for optimizing the location of renewable energy plants. The proposed approach is composed of fuzzy analytic hierarchy process (FAHP) and fuzzy data envelopment analysis (FDEA). The FDEA and FAHP methods are used to select the preferred location. The results of FDEA are validated by DEA, and then it is employed for ranking of location of renewable energy plants and the best α-cut is selected based on the test of Normality. Also, FAHP that is a method based on expert opinion is used for ranking. Five kinds of renewable energies including solar, wind, geothermal, biofuel and hydrogen and fuel cell are considered. The most related criteria are identified from the literature. The intelligent approach of this study is applied to an actual location optimization of renewable energy plants in Iran. In the proposed case study, in some cases FDEA and FAHP select the same alternatives, and for some other cases different alternatives are preferred by these two methods. According to the obtained results, the proposed approach of this study is ideal for renewable energy plant location optimization with possible ambiguity and uncertainty. The aim of this study is helping managers to select optimal locations for renewable energy plants when experts' opinions are available or not.

Keywords: Fuzzy Data Envelopment Analysis (FDEA), Fuzzy Analytic Hierarchy Process (FAHP), location optimization, renewable energy unit, Uncertainty

1-Introduction

Energy is a necessary input for social and economic development which the demand for it, has increased excessively, particularly in emergent countries. To satisfy the energy requirements of all activities, the energy planning, attempted to find a set of sources and conversion devices with an appropriate optimization adapting approach (Hiremath, Shikha et al. 2007). They demonstrated how different types of energy planning and optimization approaches, supply demand models and resource models and neural techniques have been considered and applied at a decentralized level. Making an energy planning decision involves a process of balancing diverse and sometimes conflicting aspects between ecological, social, technical, economic and etc., were criterion over space and time (Kaya and Kahraman 2010).

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Data Envelopment Analysis (DEA) is a well-known non-parametric methodology which can be applied to measure the relative efficiency of a group of decision making units (DMUs). Based on strength points of DEA methodology, Arocena (2008), in the electricity industry, investigated the degree of vertical integration, diversification and scale. In the same study, in order to determine the efficiency-based ranking of energy companies, Toshiyuki Sueyoshi and Goto (2012) discussed an integrated utilization of DEA, for assorting energy companies into efficient and inefficient classes based upon their efficiency scores and ranks. Finally, DEA- DA (Discriminant Analysis) is used to evaluate their efficiency scores and ranks. Also, to support energy planning for improving renewable energy sources (RES) utilization, an evaluation approach is introduced by Mourmouris and Potolias (2013). In the introduced assessment approach, for supporting energy planning in the concern area with all qualitative and quantitative evaluation aspects consideration, a multi-criteria approach is used (Mourmouris and Potolias 2013). In order to rank different renewable and non-renewable electricity production plants, using wind, solar, geothermal, biomass, hydropower (i.e., renewable sources), nuclear, oil, natural gas and coal, Stein (2013) extended a model for decision makers on four comprehensive criteria clusters include financial, technical, socio-economic-political and environmental. The model constructed by AHP with experimental data from government and academic sources. The result demonstrated that financial incentives for solar, wind, hydro-power and geothermal were sound and should be developed.

Moreover, Azadeh et al. (2011) proposed an integrated mathematical framework hierarchical DEA methodology hierarchical DEA methodology. Afterward, due to the DEA approach should be verified and validated, two robust multivariate methodologies namely, PCA and NT are implemented. The introduced framework, help the energy policy makers to choose the best possible location for constructing wind power plants with lowest possible cost. In the same study, Azadeh et al. (2008) identified a method for selecting suitable locations of wind plants by using an integrated hierarchical DEA methodology. To evaluate the strategic energy technologies against high oil prices, Lee et al. (2013) proposed the integrated two stage multi-criteria decision making (MCDM) technique which combined the fuzzy AHP methodology and DEA approach together. Also for identification of optimum location of solar plants with acceptable noise, non-linearity and complexity, a flexible Neuro-fuzzy framework is introduced and developed by Azadeh, Sheikhalishahi et al. (2011). The proposed approach was a hybrid technique using artificial neural network (ANN) and fuzzy data envelopment analysis.

In this paper an integrated approach consists of fuzzy data envelopment analysis (FDEA) and Fuzzy data envelopment analysis (FAHP) is applied for ranking and assessment of potential place for locating renewable energies. In some real world problems, the data for evaluation of DMUs are often not precisely defined and may be cannot accurately measured (Azadeh et al., 2011). This means that the inputs and outputs are uncertain and fuzzy. Therefore FDEA is used to overcome this weakness. Furthermore in some cases decision makers have different preferences which nonparametric methods, such as FDEA, are incapable of handling them. Thus FAHP is applied to deal with these kinds of problems. The preferred model is selected based on test of Normality according to central limit theorem, because the data are collected from various sources and are associated with accumulated error.

2-An integrated fuzzy AHP- fuzzy DEA approach

Despite the difficult conditions of access to accurate and unbiased information in Iran, the required data is collected and used. This problem could be uncertain, complex and nonlinear, also in most cases, we need to collect data in fuzzy environment. So, to alleviate these conditions, FDEA and FAHP methods, that first method is a non-parametric method and another is according to the experts, are used. Due to the nature of the problem, using FDEA (a non-parametric method) and FAHP (a method based on expert opinion) could be very appropriate. The roadmap of this study is shown in figure 1.

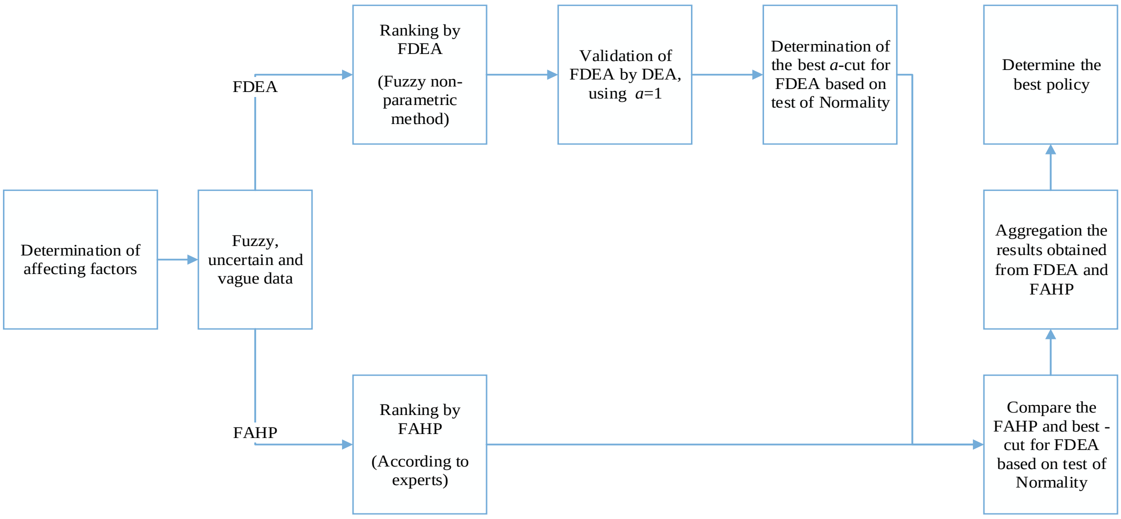

Fig 1. The roadmap of study

The importance weight of each criterion is achieved by either a direct-assignment based on expert's experiences or by considering pair wise comparisons of criteria. In this paper, to evaluate the importance of the resources, expert uses the triangular fuzzy numbers. For this purpose Chang's (Chang 1996) extensive analysis is applied.

In many studies, FDEA are used for performance assessment (see Lertworasirikul, Fang et al. (2003), Jahanshahloo, Soleimani-Damaneh et al. (2004) and Wen and Li (2009)). In this paper the FDEA model developed by Jahanshahloo, Soleimani-Damaneh et al. (2004) is used.

The aim of the model is to increase the value to zero. The expression in the objective function wants to have a negative value, consequently, the model tries to maximize this value to zero by considering different constraints. Additional details regarding the model are described in Jahanshahloo, Soleimani-Damaneh et al. (2004). The FDEA was applying with different α –cuts, then, the ranking of FDEA using non fuzzy inputs (i.e., $\alpha = 1$) have been compared with the ranking of DEA ones. The value of α ($0 \leq \alpha \leq 1$) indicates a degree of uncertainty. As α gets closer to 0, the uncertainty of the given indicators gets higher and the status of certain system changes to fuzzy, and in contrast, with increase the value of α from 0 to 1, the certainty of the system also increases. The FDEA is more capable than the DEA method, because it can handle the ranking and assessment of fuzzy and non-fuzzy data.

3-An application: Renewable energy planning of Iran

At first, a brief description of a number of different types of renewable energy and review of the renewable energy situation in Iran, which represents tremendous value to exploit these renewable sources in Iran, is listed below.

Geothermal (E1): Geothermal energy is a renewable energy that can be extracted from the temperature of the hot molten mass destruction and radioactive materials found in the depths of the earth are obtained.

Solar (E2): Solar energy is the most unique renewable energy source in the world and is the main source of all of the available energy on Earth. Solar energy in the form of direct and indirect could be converted to other forms of energy.

Wind (E3): Conversion of wind energy into another form of energy that is very useful, such as electricity (using wind turbines), mechanical energy (for example, in the windmills or wind pump) or by drift boats and ships (for example, in sailing boats), known as wind power.

Hydrogen and fuel cell (E4): A fuel cell converts chemical energy into electrical energy. This conversion is direct, therefore the efficiency is high.

Biofuel (E5): Biofuel is any fuel that has obtained from biomass, more recently organisms or their metabolic byproducts, for example manure from cows.

Based on literature review of Wang et al. (2009), the criteria assessment of energy source and site selection problems, can be classified into four principal categories. The criteria used in this study are briefly described as follows (Wang et al., 2009).

- Energy production capacity (C1): this citeria quantifies the total energy produced by power plants (Cavallaro and Ciraolo 2005). In other hand, Wang, Jing et al. (2009) introduced energy production capacity (C1) as the amount of electricity that it generates over a period, divided by the amount of electricity it could have generated if it had operated at full power over the period.
- Technological maturity (C2): technological maturity is a criteria to assess the used technology of the energy system (Beccali et al. 2003), and this criteria is evaluated using a qualitative measure (Cavallaro and Ciraolo 2005).
- Investment cost (C3): this criterion consists of all costs relating to the purchase of mechanical equipment, construction of roads and linkage to the national web, technological installations, engineering services, drilling and other incidental construction work (Wang et al. 2009).
- Operation and maintenance cost (C4): maintenance cost includes the funds spent for maintenance and operation cost consists of employee's wages, and the funds spent in the energy, the products and services (Wang et al. 2009).
- Impact on ecosystems (C5): this criterion refers to the potential risk to ecosystems caused by production of the diverse projects included in the strategies and is determined in qualitative terms.
- Land use (C6): the environment and landscape matters are affected by the land occupied by energy systems, directly, so the land needed by each plant is an issue of great concern for their evaluation.
- Social acceptability (C7): according to the hypothesized realization of the projects under review from the consumer viewpoint, this criterion expresses the overview of opinions related to the energy systems by the local population.
- Job creation (C8): energy supply systems hire many people during their life cycle, from construction and operation until decommissioning. In the decision making process of local governments, to evaluate their contributions this criteria are indispensably considered (Wang, Jing et al. 2009).

It should also be noted that access to accurate and reliable information needed for this study was very difficult in Iran. Thus fuzzy theory is applied to handle this problem. Nevertheless, the necessary data used in the proposed model, were collected from the National Statistics Bureau of Iran. In this study, 25 locations that considered as alternatives are Zabol, Shiraz, Chabahar, Mashhad, Oroumieh, Bam, Boushehr, Isfahan, Konarak, Birjand, Ahvaz, Zahedan, Larestan, Tehran, Minab, Tabriz, Yazd, Kermanshah, Amol, Jiroft, Karaj, Eghlid, Rasht, Dehloran and Kahnuj.

4-Results and analysis

First, after introducing the evaluation criteria ($C_1, \dots, C_8$) and energy sources ($E_1 \ \dots, E_5$) the fuzzy AHP method is applied. Eventually the normalized weight vector of renewable energy sources is obtained. The FAHP that is a method based on decision making opinion, for ranking 25 places and for 5 different types of renewable energy. Via the Chang's (Pires, Chang et al. 2011) extent analysis the weights of each energy resource are obtained. Note that, after collecting the required data, it was found that the value of C2 (technological maturity) for all alternatives (locations) are equal. Consequently, these criteria did not have significant effect on the ranking process. The land required and the number of people that hired during the life cycle of each type of renewable energy, are totally unique for each type of energy and only depends on the type of renewable energy system but should be considered because they are very important factors. The weights that considered for C1, C3, C4, C5, and C7 are equal to 0.251, 0.197, 0.197, 0.173, and 0.179, respectively. The weight of C2, C6, and C8 are 0.0, because value of C2 is equal for all alternatives and C6 and C8 did not depend on different locations (alternatives).

Secondly, the fuzzy DEA that is a non-parametric method is used to ranking alternatives. The inputs and outputs of this method should be determined. So that, the indices that are seeking to minimize them, consider as inputs, and outputs are indices that we want to maximize them. Consequently, C1, C2, C7 and C8 are considered as outputs and the inputs are C3, C4, C5 and C6, and the DMUs are abovementioned 25 locations.

Technical efficiency (TE) is a level of performance that determines how the locations or alternatives, based on an assumed set of technical, economic, environment, and social criteria, relate specific outputs to a set of given inputs. In Jahanshahloo model (Jahanshahloo et al. 2004) for FDEA, TE is the optimal value of objective function. To validate the model of fuzzy DEA at $\alpha=1$, the results of ranking compared with DEA results (figure 2). For this purpose, the correlation coefficient between the ranking results of both methods DEA and FDEA is calculated. Nonparametric statistics, in contrast with parametric statistics, are the statistical methods that try to do the least assumptions in the data analysis. In, other words, nonparametric statistical models are infinite dimension. Thus, in this case study, we do not include the typical parameters, of mean, variance, standard deviation, etc. The value of this correlation coefficient indicates the ability to express one variable as a function of another variable is monotonic. Perfect correlation (-1 or +1) occurs when the dependent variable of the other variable is monotonic (Corder and Foreman 2009).

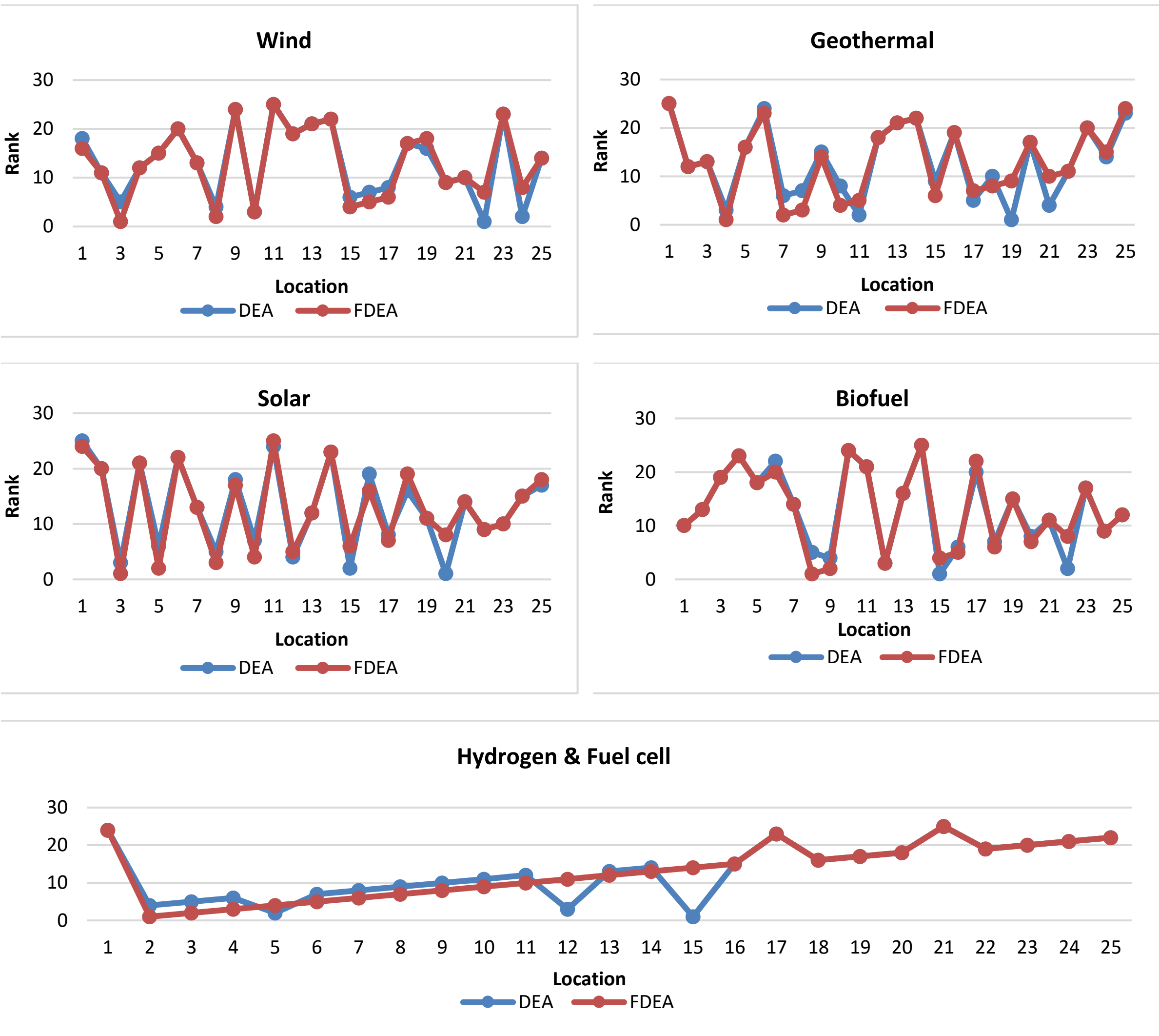

Fig 2. The results of DEA and FDEA ($\alpha=1$)

Table 1 shows the values of correlation coefficient associate with different types of renewable energy resources at five levels of α-cuts. According to obtained values of correlation coefficient, the results of FDEA have been verified and validated by DEA with high level of confidence.

Table 1. Spearman correlation scores between DEA and FDEA for renewable energy resources

Renewable energy	Level of α-cut				
	0.1	0.3	0.5	0.7	1.0
Geothermal	0.929	0.942	0.962	0.962	0.930
Solar	0.951	0.964	0.951	0.964	0.953
Wind	0.973	0.978	0.965	0.978	0.957
Hydrogen and fuel cell	0.712	0.678	0.935	0.848	0.888
Biofuel	0.928	0.945	0.973	0.992	0.971

Finally, to comparison the results of FAHP and FDEA, the best level of α-cut for each renewable energy resource should be determined. For this purpose, Normality test has been applied. The results of Normality test have been shown in table 2. The Shapiro–Wilk test is one of the well-known tests for checking normality. This test compared to other tests (such as Kolmogorov-Smirnov Test) is very appropriate when the sample size is less than 50, but it can also handle sample size as large as 2000. In this test the null-hypothesis (H0) is that the distribution of ranking scores is normal, and the alternative-hypothesis (H1) is unlike the null-hypothesis. The H0 has been rejected (i.e. there is evidence indicating that the distribution of ranking scores do not normal.), when the p-value is less than chosen Statistical significance (alpha-level). And conversely, when the p-value is greater than the selected alpha-level, there is no reason to reject the H0. For each renewable energy resource, the best level of α-cut has been selected based on the maximum p-value, note that if there was more than one maximum value for p-value, one of them will choose arbitrarily.

Table 2. P-values of Normality Test

Renewable energy	Level of α-cut				
	0.1	0.3	0.5	0.7	1.0
Geothermal	0.033	0.019	0.009	0.009	0.000
Solar	0.188	0.138	0.188	0.138	0.003
Wind	0.094	0.074	0.041	0.022	0.004
Hydrogen and fuel cell	0.225	0.167	0.097	0.042	0.008
Biofuel	0.225	0.087	0.025	0.008	0.002

According to the results, for all resources of renewable energy, we can chose α = 0.1 because, for all renewable energy resources, the maximum p-value associated with this α. This proves the existence of tremendous uncertainty and noise in the data set. Therefore, if DEA method was used for ranking of DMUs, the results of ranking could be misleading. Therefore, the results of FAHP were compared with the results of FDEA method at α = 0.

According to the results, however for biofuel and geothermal energies results of FDEA and FAHP are the same, for other energies different results are obtained. This shows the preferences of decision makers were different from the results of FDEA, which is a non-parametric method.

For each renewable energy resource, as mentioned before, the best model for ranking the locations is chosen by applying Normality test. The p-values obtained from Shapiro–Wilk Test for FAHP and FDEA are shown in table 3. Based on these p-values, we can select the preferred model.

Table 3. Shapiro-Wilk Test to determine the preferred model

	***P*-value of FAHP**	***P*-value of FDEA (α = 0.1)**	**Preferred Model**
Geothermal	0.497	0.033	FAHP
Solar	0.915	0.187	FAHP
Wind	0.601	0.094	FAHP
Hydrogen and fuel cell	0.401	0.227	FAHP
Biofuel	0.068	0.227	FDEA

According to results obtained from Shapiro-Wilk (table 3), the best model for ranking the locations for each type of renewable energy resource is determined. For Geothermal, Solar, Wind, Hydrogen and fuel cell, FAHP is selected as the preferred. This selection shows that for these 4 types of renewable energy, the opinion of experts is significant. For Biofuel, the preferred model is FDEA at $\alpha = 0.1$.

5- Conclusion

In many developing countries energy projects expressed that renewable energy sources can have a significant effect to the economy by providing the energy required for education, cooking, space heating, and lighting and also for creating new businesses and employment. Consequently, recently, regarding to Iran's renewable energy sources capacity the attention to the non-fossil energy resources, are extremely increased. In this paper, an integrated Fuzzy AHP- Fuzzy DEA approach has been proposed for ranking the locations and determine the best type of renewable energy unit for these locations by fuzzy DEA and fuzzy AHP. After collecting the required data, using FDEA and FAHP to ranking places and for validating the results of FDEA at $\alpha = 1$ using DEA by Spearman correlation method. In low degree of uncertainty and vagueness the results of ranking by the DEA and FDEA are relatively similar. Finally, the preferred model for ranking the alternatives (locations) is chosen based on Shapiro–Wilk test. The data sets that are required in this case study, are collected from different resource and there accumulates error among them, so, the Normality test should be used. The preferred model for ranking the Geothermal, Solar, Wind and Hydrogen and fuel cell, is fuzzy AHP and for Biofuel, the Fuzzy DEA at $\alpha = 0.1$ is preferred. But, it is possible for ranking another case study, different methods are selected. This shows how decision makers' preferences may affect the preferred location selection. However if the decision makers have inconsistent viewpoints, or they were neutral about different criteria, FDEA may be used to select the preferred location.

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