

Chapter 10

Strategic Analysis of Solar Energy Pricing Process with Hesitant Fuzzy Cognitive Map



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Abstract Sun is the leading renewable energy source for satisfying energy demand. Solar energy systems, which have direct and indirect energy generation technologies, require high initial costs and low operation costs. The right determination of solar energy price has an important role on efficient solar energy investment decisions. In this study, the critical factors for the solar energy price are defined and the causal relationships among them are represented with a Hesitant Fuzzy Cognitive Map (HFCM) model. The causal relations among the factors and the initial state values of the factors are defined with the linguistic evaluations of the experts by using Hesitant Fuzzy Linguistic Term Sets (HFLTSSs). The linguistic expressions are converted into Trapezoid Fuzzy Membership Functions (TFMFs). The obtained HFCM model is used for simulating various scenarios, and the equilibrium state values of the factors are obtained. The results indicate that the factors affecting solar energy systems have an important effect in determining the solar energy price. The solar energy price adapts to the general energy price market in the long term.

10.1 Introduction

Energy which allows people to live a more productive life is basically provided with six power sources and they can be transformed from one form into another as mechanical, chemical, thermal, radiant, nuclear, and electric. The primary energy sources commonly used in the world (85.52% of total energy consumption) are fossil based (coal, gasoline, natural gas) (BP 2017). The increase in fossil fuel consumption leads to the increased atmospheric release of greenhouse gases, especially CO₂. Global warming and climate changes caused by greenhouse gases are an essential part of the economic, social and environmental problems. Therefore,

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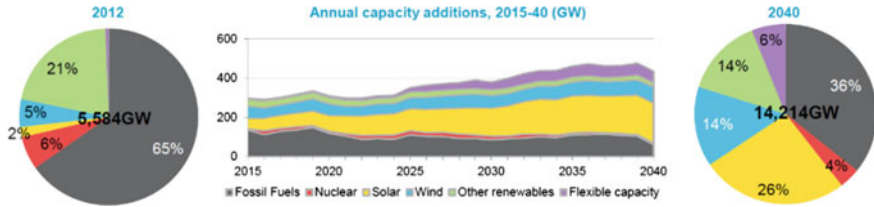


Fig. 10.1 Annual capacity additions and expectations until 2040 (Bloomberg New Energy Finance 2015)

the use of fossil-based fuels in energy-intensive conditions is the most precise indication of the human impact on climate change (Stern 2015). Greenhouse effect, global warming, and climate change have led governments to turn to renewable energy sources (sun, wind, hydroelectric, biomass) as an alternative to fossil energy sources. The National Science Academies of the G8 countries reported that a joint action against climate change should be undertaken and urged governments to reduce CO₂ emissions by 50% below 1990 levels by 2050 (Academies 2009).

In the long run, production of electricity from coal, oil and natural gas is expected to be replaced by entirely renewable energy sources (Fig. 10.1). However, the significant disadvantages of renewable energy production against traditional energy sources are that they are more expensive and less reliable (Conkling 2011). The difficulties in using renewable resources are also as follows: political uncertainty, the tendency of countries to move away from FITs and green certificates, changes in subsidies and the need to integrate renewable-based systems with existing power plants.

In order to promote the use of solar energy, which is the most important renewable energy source, it must be able to compete with other renewable and traditional energy types. Regulatory policies, fiscal incentives, and public financing bases shape the countries' support for developing solar energy capacity. For example, Turkey uses feed-in tariff/premium payment, biofuels obligation/mandate, capital subsidy, grant, or rebate, and public investment, loans, or grants methods as promotion policy (Crawley 2016).

Price, which is the most important competitive factor in energy and all other markets, is an important measure for the adoption and diffusion of solar energy technologies. Therefore, the fundamental factors that are effective in solar energy pricing are defined and the relationship between them is modelled in this study. The national and international factors that influence solar energy pricing in the energy market include uncertainty and hesitancy. Hence, the HFCM model is utilized for developing the causal relationships of solar energy pricing. The causal relationships among the active factors in the solar energy HFCM pricing model are defined, and their effects on the solar energy pricing are reflected in the equilibrium state.

The organization of the chapter is as follows: Sect. 10.2 explains the pricing in solar energy, the effective factors in the solar energy system. The HFCM model and its preliminaries the FCM, the hesitant fuzzy set and the HFLTS subjects are mentioned in the Sect. 10.3. The processing process and calculation methods of the

HFCM model are mentioned in Chap. 4. Chapter 5 gives the results of simulation evaluations of the solar energy price based HFCM model developed with two different scenarios. The study is completed in the conclusion section with the general results and future studies.

10.2 Solar Energy Pricing

Governments should access sustainable, quality and cheap energy sources to support and sustain their economic and social development. Increasing population leads to further increase in demand, hence, new energy generation methods are developed to meet this increasing demand. However, the use of fossil-based energy sources to meet rising energy demand creates environmental and economic problems (Thomas et al. 2011). Therefore, the countries have turned to renewable energy sources, especially solar with the support of national and international decisions and agreements. India, for example, has set a goal of increasing solar energy capacity from 5.2 GW in 2016 to 100 GW by 2022 (Council 2016). Similarly, Turkey has set a target to increase the solar energy capacity of 2 GW at the end of 2017 to 5 GW in 2023 (PV-Magazine 2017).

The price of energy is the most critical determining factor for the acceptance of renewable energies by the society and investors. Correct pricing is advantageous for energy providers to optimize capacity planning and for consumers to minimize energy costs. Energy pricing and forecasting of energy needs allow appropriate energy capacity planning, financing technologies and investments in energy diversity, and enabling investors and governments to develop stable policies (Mir-Artigues and Del Río 2016). In particular, the economic depression and poverty caused by the rise in energy prices in the 1970s and 1980s led to the development of new policies and models based on energy availability and cost (Timilsina et al. 2012). Knowing the factors that affect energy prices and understanding their impact on the energy market is the starting point for solar energy pricing.

The energy price (EP) is determined by the installed capacity, not by the actual energy production (Zatzman 2012). The total energy price is calculated taking into account factors that cause economic effects and components based on performance. Factors defined in the price calculation include uncertainty, which may vary locally and temporally.

Factors affecting solar energy pricing

In this section, factors affecting solar energy pricing are defined, and causal relationships among factors are explained in the model. Causal relationships are evaluated and how the factors affect each other in the long run are observed under the HFCM model. Thus, factors that determine solar energy prices and the causal relationships between the factors shown and the decision making processes of the government and investors in the long term accurately directed.

The main factor driving a country to use renewable energy from fossil energy consumption is the conscious governments know that fossil fuels are behind their country's environmental, economic and social problems (Environmental Effects, EE and Eco-social Effects, ESE). The anticipation of the deterioration of agricultural production and living conditions caused by the change of climate change and vegetation cover is at the basis of environmental concerns. Governments develop national and international directive laws and regulations (Global treaties, GT such as Kyoto Protocol) to manage the use and widespread of renewable energies in the community. Laws and regulations differ among countries according to their renewable energy potentials (Çoban and Onar 2017). National regulations are severely affected by international agreements and supportive policies.

The trend towards renewable energies revealed the technical and technological infrastructure problems (IP). Having different characteristics of the environmental conditions of the energy plants reveals the infrastructure requirements of the plants and affects the initial costs and solar pricing. Therefore, the use of renewable energy has a significant price disadvantage against the use of fossil based energy. In contrast, governments' policies to support renewable energies provide price competition against fossil fuels.

The supportive laws and legislations (SLLs), which aim to generate electricity from solar energy source, specify the procedures and principles for the realization of electricity generation in the country. Incentives (Fig. 10.2), which are applied in many countries around the world, are aimed at eliminating energy dependency by supporting renewable energy sources. Supporting, encouraging and inhibiting the solar energy investments can be covered by the cost of energy companies that do not produce renewable energy (Ministry 2017). This situation, which causes fluctuations in the general energy prices, causes solar energy prices to fluctuate in an indefinite range.

The most common support scheme for the development of solar energy systems is feed-in tariff (FIT). FIT for entire production (FITEP) guarantees that the electricity generated from a solar energy system and transmitted to the grid is purchased

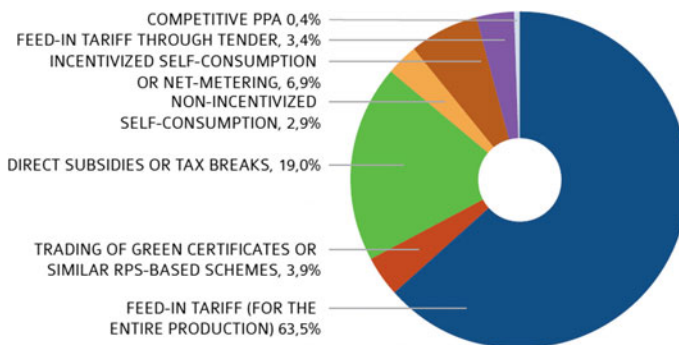


Fig. 10.2 Historical market incentives and enablers (IEA 2016)

at a predefined price for a specified period (Crawley 2016). For example, the purchase of electricity generated by facilities that produce electricity using solar energy sources is committed by the state at a fixed price (0.133 \$/kWh) for ten years in Turkey (Ministry 2017). The support provided by the FIT policy is financed by tax revenues or by taxation on companies generating energy without renewable energy.

The accurate determination of support price and duration values in FIT plans has a critical precaution for solar energy and general energy pricing. High-priced and long-term support leads to a decline in energy prices and a deterioration of the market balance (Spain 2008, Czech Republic 2010, Italy 2011) (Mir-Artigues and Del Río 2016). In addition, if domestic producers supply mechanical and/or electromechanical components used in grid-connected solar energy generation facilities, these facilities benefit from price supports. For example, if the solar energy plant established in Turkey supplies its equipment and materials from domestic manufacturers, it wins an additional domestic contribution to FIT for five years (Ministry 2017). If the PV modules in the installation of the PV solar energy plant are produced in Turkey, 1.3 US cents/kWh domestic production contribution is given for five years.

FIT with tender (FITT) is an alternative method of providing FIT support to reduce the cost of PV electricity. Competition with the tender procedure enables to draw the solar energy price to the lowest possible level and to reduce margins. This support method reflects how low the bids can be under competitive bidding conditions. Low bids can only be realized if the market has low capital costs, low component costs, and a low risk (IEA 2016).

The direct capital subsidy (DS) is the most straightforward way for governments to promote solar energy installations. The system investment cost is made attractive with this single-process subsidy method (CEDE 2014). Direct capital subsidies are the financial support through taxation (tax breaks, TB) for upfront investments in solar energy systems according to their off-grid and on-grid connections (Crawley 2016).

The Renewable Portfolio Standard (RPS) is a market mechanism based on a plan to gradually increase electricity generated from renewable energy sources (wind, biomass, geothermal and solar). Competition between renewable energies is achieved through this market-based approach. Thus, the use of renewable energy sources is continuously promoted and the cleanest energy is achieved at the lowest price (Scientists 2015). RPS and related approaches determine a share of electricity that must be generated from a particular renewable energy source. This incentive plan allows renewable electricity producers to charge a market-based fee for the electricity they give to the grid (Crawley 2016).

Self-consumption is the independent supply of individual energy needs from the small scale solar energy systems established on the residential roof. Although self-consumption systems have high costs compared to utility-scale systems, their price advantages provided by individual investors (non-incentivized self-consumption, SCNI), in the long run, can make their use even more widespread. Sustainable building regulations have increased the interest in using solar

tools (photovoltaic, solar water heater and passive solar energy) as a source of heating and electricity. The use of solar energy technologies in construction can be supported by environmental regulations and legislation to reduce the energy footprint of buildings (incentivized self-consumption, SCI). Net metering (NM) is a system that helps to arrange energy billing by following the consumed electricity by the structures and the generated electricity by the solar energy system. Electricity generated by the net-metered solar power system of the residence meets the residential energy demand primarily, and the increasing electricity is supplied to the grid. If the residential solar power system generates more electricity than needed during the billing period, net metering customers receive bill credits. The investment of solar energy is depreciated in a shorter period, and solar energy prices are affected positively with this system (IEA 2016).

Power Purchasing Agreements (PPAs) are a standard business model for meeting near-energy demands with electricity generated from grid-connected medium-sized solar power systems inbuilt. The system owner sells the generated electricity through a direct connection to the nearby consumers. Thus, consumers' demand for mains electricity is reduced, and a lower selling price for electricity generated from solar energy arises. The system based on profitability is affected by the electricity cost of the grid that is shaped by the electricity supply-demand (Crawley 2016; IEA 2016).

Technical and political support increases the installation of solar energy facilities and solar energy generation capacity. The increase in the generation capacity of solar energy contributes to the stabilization of total energy demand and energy supply (ES) and determines the price of solar energy in the energy market. Improvements in the solar energy technology (SETI) increase solar energy production potential by reducing the costs of solar energy installation and by developing the infrastructure requirements for installation. Economic components (EC) for solar energy pricing can be shaped with capital cost, return on equity, interest on loan, depreciation, operation and maintenance expense, insurance, taxes, service charges, and cost escalation factor (Thomas et al. 2011). In addition to these critical economic factors, installed capacity, capacity utilization and penalty factors have an important influence on pricing.

The ever-increasing world population brings with it the increase in production and consumption. The total amount demanded of energy, which is the basic element of production and consumption, is called energy demand. In order to meet the rising energy demand, it is necessary to use the sun and other energy resources together to generate energy supply. Energy prices (as a combination of renewable and non-renewable energy prices, REP/NREP) are an important factor in achieving a balance between energy demand and supply. The installation of new solar power plants and the increase in the total installed solar capacity contribute to energy supply and indirectly affect energy prices.

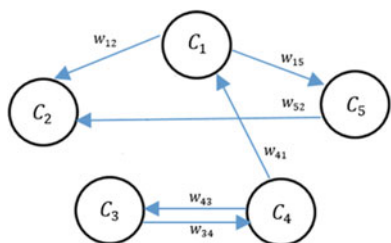
The support and encouragement for the dissemination of solar energy reduce the availability of existing and widespread fossil-based energy production systems and equipment. In this case, the perceived damage of fossil-based investments, existing industrial system, and production technologies lead to the emergence of anti-solar

energy policies. However, the ease of transportation and storage of fossil-based energies causes serious cost disadvantages to solar-based energy systems.

10.3 Fuzzy Cognitive Maps

FCMs, which are an extension of cognitive maps with fuzzy logic, enable recognizing causal relationships among components in complex systems. Fuzzy Cognitive Maps (FCM), fuzzy graphical structures representing causal reasoning, are defined by Kosko (1986). An FCM is represented with signed and directed graphs showing concepts and causal relationships among concepts. In graphical notation, concepts are represented by nodes and denoted as C_i , and causal relations among nodes are represented by weighted edges and denoted as w_{ij} . The weight value of the edges expresses the fuzzy strength of causal relations and is represented by fuzzy numbers. Graphical representation of complex systems with FCM allows visual representation of concepts and directional relationships among them.

Figure 10.3 represents a simple FCM model with five members (C_i) and six weighted edges (w_{ij}) between these members. Weights expressed regarding the causal relationship between concepts are expressed as the values between $[-1, 1]$. The positive and negative sign of relationship weight expresses the direction of the relationship between concepts. The absence of a causal relationship between concepts indicates that the weight value is zero. The change in any concept in the FCM model, which has the fuzzy feedback loop feature, causes to change the current state of the other concepts in the system. If all the factors in the model reach an equilibrium state, the feedback loop process is terminated (Kosko 1997). Since the factors in the FCM are not self-feedback (i.e., no self-causal relationship), the diagonal value of the weighted relationship matrix is zero. Subjective information based on expert knowledge and experience or objective information obtained through methods such as literature review is used to identify the concepts and fuzzy causal relationships between concepts in the FCM (Çoban and Onar 2017).



	C_1	C_2	C_3	C_4	C_5
C_1	0	w_{12}	0	0	w_{15}
C_2	0	0	0	0	0
C_3	0	0	0	w_{34}	0
C_4	w_{41}	0	w_{43}	0	0
C_5	0	w_{52}	0	0	0

Fig. 10.3 A sample FCM and relation matrix

Some structural criteria reflect the model factors and general model characteristics. Transmitter refers to the factor affecting other factors but not being affected by other factors. Receiver refers to the factor affected by other factors but not affecting other factors. Ordinary refers to the factor affecting other factors and influenced by other factors. Centrality represents the sum of the influence values of the factor (Papageorgiou 2013). The total value of the relationships that are directed to a factor is defined as “in-degree.” The sum of relations from one factor to the other is called “out-degree.”

The weight values of causal relations in the FCM can be determined using triangular, trapezoidal, sigmoid, Gaussian functions or fuzzy linguistic terms. The FCM model operates using fuzzy arithmetic operators, and defuzzification methods (weight centers, center area, and weighted average method) are used to transform the fuzzy values reached in the steady state to crisp values in the range $[-1, 1]$.

A_i^t denotes the state value of the concept C_i in time t , and the general state values for all concepts in FCM can be shown in the form $A^t = [A_1^t, A_2^t, \dots, A_n^t]$. The next state value of concept i (C_i) reaches after each iteration is defined as:

$$A_i^{t+1} = f\left(\sum_{j=1}^n A_j^t w_{ij} + A_i^t\right) \quad (10.1)$$

where $f(\cdot)$ is the threshold function that is used to transform the sum of the previous state value (A_i^t) and the total causal effects. The most commonly used transformation (threshold) functions are hyperbolic tangent and sigmoid functions that get values in the range $[0,1]$ and $[-1,1]$ respectively.

$$f(t) = \frac{1}{1 + e^{-\lambda t}} \quad (10.2)$$

$$f(t) = \tanh(\lambda t) = \frac{e^{\lambda t} - e^{-\lambda t}}{e^{\lambda t} + e^{-\lambda t}} \quad (10.3)$$

The optional lambda parameter ($\lambda > 0$) in the functions is used to determine the appropriate slope of the function. The value x represents the internal calculation performed on the new state vector. If the difference between the two state values ($A_i^{t+1} - A_i^t$) for each concept is 0.001 or less, the iterations are terminated, and the final state is called as a steady state (Papageorgiou 2013).

10.3.1 Preliminaries

10.3.1.1 Hesitant Fuzzy Sets

Fuzzy set theory was developed by Zadeh (1996) to model and calculate uncertainty and vagueness using mathematical methods. The fuzzy set theory, which is oriented towards solving complex everyday life problems, has been applied to a wide range of scientific fields such as decision theory, energy management, and artificial intelligence methods (Papageorgiou 2013; Michael 2010). New extensions of fuzzy sets are developed to produce more accurate approaches and solutions to the complex and ambiguous problems encountered in everyday life (Mizumoto and Tanaka 1976; Atanassov 1986; Torra 2010). The Hesitant Fuzzy Sets (HFSs), developed by Torra (2010), are aimed at dealing with the situations where more than one value of a membership of the fuzzy clusters may be possible. In HFS, a function is defined that returns a set of member values for each element in the domain (Torra 2010).

HFS, defined on the reference set (X), is expressed as a function (h) that returns a subset in the range $[0,1]$. The mathematical representation of the expression is as follows:

$$h : X \rightarrow \{[0, 1]\} \tag{10.4}$$

The association of HFSs for a set of N membership functions is represented as $M = \{\mu_1, \mu_2, \dots, \mu_N\}$ and shown as:

$$h_M : M \rightarrow \{[0, 1]\} \text{ and } h_M(x) = \cup_{\mu \in M} \{\mu_x\} \tag{10.5}$$

The upper and lower bound of the hesitant fuzzy set h is given as Torra (2010):

$$h^-(x) = \min h(x) \text{ and } h^+(x) = \max h(x) \tag{10.6}$$

Some basic operations (complement, union, and intersection) of the HFSs can be defined as follows (Torra 2010):

$$h^c = \cup_{\gamma \in h(x)} \{1 - \gamma\} \tag{10.7}$$

$$(h_1 \cup h_2)(x) = \{h \in (h_1(x) \cup h_2(x)) | h \geq \max\{h_1^-, h_2^-\}\} \tag{10.8}$$

$$(h_1 \cap h_2)(x) = \{h \in (h_1(x) \cup h_2(x)) | h \leq \min\{h_1^+, h_2^+\}\} \tag{10.9}$$

where h represents the hesitant fuzzy set.

10.3.1.2 Hesitant Fuzzy Linguistic Term Sets

Linguistic knowledge using words or phrases is applied to solve daily life problems which cannot be expressed by numerical values. The linguistic expressions used to identify and solve problems are a tool that best reflects people’s perceptions and knowledge (Zadeh 1975). The fuzzy set theory is dependent on linguistic variables which are fuzzy variables. The fuzzy linguistic approach, which uses a single language term, is insufficient to express and evaluate language variants involving hesitation. HFLTSS have been proposed as a solution to these common problems by Rodriguez et al. (2012).

An ordered finite subset of consecutive linguistic terms of linguistic term set $S = \{s_0, s_1, \dots, s_g\}$ is represented with H_s (HFLTS). For example, a sample HFLTS can be defined as $H_s = \{s_2, s_3, s_4\}$ where linguistic term set S is determined as $S = \{s_0 : \text{nothing}, s_1 : \text{very low}, s_2 : \text{low}, s_3 : \text{medium}, s_4 : \text{high}, s_5 : \text{very high}, s_6 : \text{perfect}\}$. The upper/lower bounds (H_{S^+}, H_{S^-}), complement (H_s^c) and basic operations of the HFLTSS (H_s, H_s^1, H_s^2) are shown as:

$$\begin{aligned} H_{S^+} &= \max(s_i) = s_j, s_i \in H_s \text{ and } s_i \leq s_j \forall_i \text{ and} \\ H_{S^-} &= \min(s_i) = s_j, s_i \in H_s \text{ and } s_i \geq s_j \forall_i \end{aligned} \tag{10.10}$$

$$H_s^c = S - H_s = \{s_i | s_i \in S \text{ and } s_i \text{ not } \in H_s\} \text{ and } (H_s^c)^c = H_s \tag{10.11}$$

$$(h_1 \cap h_2)(x) = \{h \in (h_1(x) \cup h_2(x)) | h \leq \min\{h_1^+, h_2^+\}\} \tag{10.12}$$

Generated new values for these operations also will be an HFLTS.

10.3.1.3 OWA Operators

Collecting a set of information to obtain a new information is called aggregation and the operators used for this purpose are called the aggregation operator (mean, arithmetic mean, weighted arithmetic mean) (MDAI 2014). The ordered weighted averaging (OWA) aggregation operator is applied to aggregate the HFLTSS and obtain a universal HFLTS.

$$OWA(x_1, x_2, \dots, x_k) = \sum_{i=1}^k l_i w_i \tag{10.13}$$

where l_i is the i . largest member of the aggregated elements x_1, x_2, \dots, x_k . w_i is a weight of the ordered i . data in $[0,1]$ interval and is defined the weighting vector W , $W = (w_1, w_2, \dots, w_k)^T$. The sum of the weights defined in W equals one as $\sum_{i=1}^k w_i = 1$ (Yager 1988). The methods (maximum, minimum, average) applied to determine the weighting values enable differentiation of OWA operators. The OWA

collection operator, introduced by Yager, had the opportunity to practice in different branches of science (Yager 1988). The ability of the OWA operator to collect and model linguistic expressions allows it to be used extensively in computational intelligence and fuzzy logic-based calculations as an aggregation operator.

The orness method can represent the degree of optimism and pessimism of the OWA operator (Liu and Rodríguez 2014). Because of this feature, orness method which is widely used in researches is also used in this study. The mathematical representation of the orness method is as follows.

$$orness(W) = \frac{1}{k-1} \sum_{i=1}^k w_i(k-i) \tag{10.14}$$

where $0 \leq orness(W) \leq 1$. $orness \geq 0.5$ condition points to optimistic OWA operators and $orness < 0.5$ state points to pessimistic OWA operators (Yager 1993).

10.4 Hesitant Fuzzy Cognitive Maps

FCM is a dynamic modelling tool that reflects the concepts and causal relationships between concepts in complex and uncertain systems. Hesitant fuzzy sets (HFS) provide ease of assessment by allowing more than one value to identify membership in a situation (Kahraman et al. 2016). HFCM is a fuzzy method that models the causal relationships of linguistic evaluations defined by HFLTS. Hesitant linguistic expressions that are natural translations of experts’ cognitive assessments with words or phrases are used to define concepts and their initial states. The process flow of HFCM is as follows:

Stage 1. Development of relationship model

Factors and the relationships between the factors of the HFCM model are determined by the common opinions of experts’ knowledge and experiences. In the model, the system members are represented by nodes (C_i), and the causal relationships between the members are indicated by directed linguistic edges. A simple HFCM in Fig. 10.4 is represented with five concepts (C_1, C_2, C_3, C_4, C_5) and six

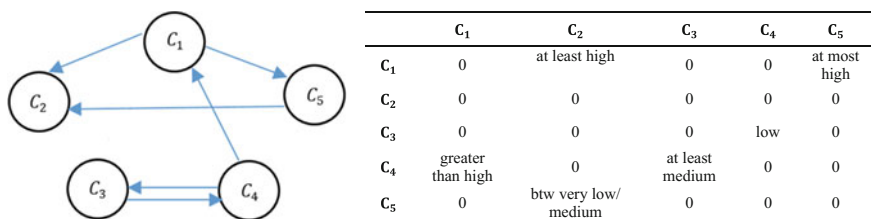


Fig. 10.4 A simple HFCMs and HFLTS matrix

directed linguistic edges. Since the HFCM does not contain any self-loop concept, their values in the weight matrix are defined as zero ($w_{ii} = 0$).

Step 2. Collection of experts' information using HFLTS

Uncertain and dynamic system conditions cause experts to ambiguously identify the concepts and relationships between concepts in the cognitive map. Hence, experts use hesitant linguistic terms to convey ideas more naturally. Natural hesitant linguistic expressions of experts are defined by using context-free grammar, G_H that is generated with 4-tuple (V_N, V_T, I, P) (Rodriguez et al. 2012; Bordogna and Pasi 1993).

Hesitant linguistic expressions are defined by using a linguistic term set where $S = \{s_0 : \text{nothing}, s_1 : \text{very low}, s_2 : \text{low}, s_3 : \text{medium}, s_4 : \text{high}, s_5 : \text{very high}, s_6 : \text{absolute}\}$ and context-free grammar. The sample hesitant linguistic statements are as follows: at most high, smaller than low, and between medium and high. Hesitant linguistic expressions provide flexibility to define and evaluate the hesitant concept and causal relationships among them.

The linguistic expressions obtained by expert evaluations must be converted to HFLTS for use in HFCM model calculations (Rodriguez et al. 2012). The transformation function, E_{G_H} developed by Rodriguez et al. (2012) is used in the conversion process. The methods applied according to the linguistic term set, S in the conversion process are as follows.

$$\begin{aligned} E_{G_H}(s_i) &= \{s_i | s_i \in S\} \\ E_{G_H}(\text{at least } s_i) &= \{s_j | s_j \in S \text{ and } s_j \geq s_i\}, E_{G_H}(\text{at most } s_i) = \{s_j | s_j \in S \text{ and } s_j \leq s_i\} \\ E_{G_H}(\text{lower than } s_i) &= \{s_j | s_j \in S \text{ and } s_j < s_i\}, E_{G_H}(\text{greater than } s_i) = \{s_j | s_j \in S \text{ and } s_j > s_i\} \\ E_{G_H}(\text{between } s_i \text{ and } s_j) &= \{s_k | s_k \in S \text{ and } s_i \leq s_k \leq s_j\} \end{aligned}$$

For example, $\{\text{medium}, \text{high}, \text{very high}\}$ is a sample HFLTS that is transformed form of the “between medium and very high” linguistic expression; $E_{G_H}(\text{between low and high}) = \{\text{low}, \text{medium}, \text{high}\}$.

Step 3. Fuzzy envelope of HFLTS

The enveloping method is used to compare the HFLTS converted from the linguistic expressions of the experts and to start the calculation processes in the HFCM model. Envelopment of an HFLTS, $env(H_S)$ is indicated by upper (H_{S^+}) and lower (H_{S^-}) bounds as follows:

$$env(H_S) = [H_{S^-}, H_{S^+}], \quad H_{S^-} \leq H_{S^+} \quad (10.15)$$

For example, the HFLTS, $H_S = \{\text{low}, \text{medium}, \text{high}\}$ of “between low and high” linguistic evaluation can be enveloped under $S = \{\text{nothing}, \text{very low}, \text{low}, \text{medium}, \text{high}, \text{very high}, \text{absolute}\}$ linguistic terms set as $env(H_S) = [\text{low}, \text{high}]$.

The OWA operator is contacted to obtain the fuzzy membership function of HFLTS and bring these membership functions together (Liu and Rodriguez 2014).

To reflect the linguistic uncertainties expressed by HFLTS, it is appropriate to use the trapezoidal membership function, $\tilde{A} = (a, b, c, d)$ in the OWA operator procedure (Delgado et al. 1998). The process stages for calculating the coefficients expressing the trapezoidal membership function are as follows (Liu and Rodríguez 2014):

Stage 1. Defining the aggregation elements

Linguistic terms are applied to calculate the parameters of the trapezoidal fuzzy membership function, $\tilde{A} = (a, b, c, d)$, as $A^k = T\{a_l^k, a_m^k, a_r^k\}, k = 0, 1, \dots, g$. The set of aggregation elements of the linguistic terms in the HFLTS $H_s = \{s_i, s_{i+1}, \dots, s_j\}$ are shown as; $T = \{a_L^i, a_M^i, a_L^{i+1}, a_R^i, a_M^{i+1}, a_L^{i+2}, a_R^{i+1}, \dots, a_L^j, a_R^{j-1}, a_M^j, a_R^j\}$.

The set of aggregation elements can be simplified with fuzzy partition under $a_R^{k-1} = a_M^k = a_L^{k+1}, k = 1, 2, \dots, g - 1$ acceptance and defined as Ruspini (1969) $T = \{a_L^i, a_M^i, a_M^{i+1}, \dots, a_M^j, a_R^j\}$.

Stage 2. Calculation of the TFMF's parameters

Parameters of the TFMF, $\tilde{A} = (a, b, c, d)$ that defines the fuzzy envelope, $env_F(H_s)$ of the HFLTS, H_s are determined using the set of aggregation elements, $T = \{a_L^i, a_M^i, a_M^{i+1}, \dots, a_M^j, a_R^j\}$. Limit values, a and d , are defined by the linguistic limits as $s_i = \min H_s$ and $s_j = \max H_s$.

$$\begin{aligned} a &= \min\{a_L^i, a_M^i, a_M^{i+1}, \dots, a_M^j, a_R^j\} = a_L^i \text{ and} \\ d &= \max\{a_L^i, a_M^i, a_M^{i+1}, \dots, a_M^j, a_R^j\} = a_R^j \end{aligned} \tag{10.16}$$

The intermediate parameters, b and c , of the TFMF are calculated using OWA aggregation operator.

$$b = OWA_{W^s}(a_M^i, a_M^{i+1}, \dots, a_M^j) \text{ and } c = OWA_{W^t}(a_M^i, a_M^{i+1}, \dots, a_M^j) \tag{10.17}$$

where $s, t = 1, 2; s \neq t$ or $s = t$. Filev and Yager's methods is used calculate the weighting vectors, W^s and W^t , in the OWA aggregation operations (Filev and Yager 1998).

The first type of OWA weights $W^1 = (w_1^1, w_2^1, \dots, w_n^1)^T, 0 \leq \alpha \leq 1$.

$$env(H_s) = [H_{S^-}, H_{S^+}], \quad H_{S^-} \leq H_{S^+} \tag{10.18}$$

The second type of OWA weights $W^2 = (w_1^2, w_2^2, \dots, w_n^2)^T, 0 \leq \alpha \leq 1$.

$$\begin{aligned} \alpha w_1^2 &= \alpha^{n-1}, w_2^2 = (1 - \alpha)\alpha^{n-2}, w_3^2 = (1 - \alpha)\alpha^{n-3}, \dots, w_{n-1}^2 = (1 - \alpha)\alpha, w_n^2 \\ &= (1 - \alpha) \end{aligned} \tag{10.19}$$

The orness measures, $orness(W^1)$ and $orness(W^2)$, are calculated with the weighting vectors as follow:

$$\begin{aligned}
 orness(W^1) &= \sum_{i=1}^n w_i^1 \left(\frac{n-i}{n-1} \right) = \frac{n-1}{n-1} \alpha + \frac{n-2}{n-1} \alpha(1-\alpha) \\
 &\quad + \frac{n-3}{n-1} \alpha(1-\alpha)^2 + \dots + \frac{1}{n-1} \alpha(1-\alpha)^{n-2} + \frac{0}{n-1} (1-\alpha)^{n-1} \\
 &= \frac{n}{n-1} - \frac{1 - (1-\alpha)^n}{(n-1)\alpha}
 \end{aligned}
 \tag{10.20}$$

$$orness(W^2) = \frac{\alpha - \alpha^n}{(n-1)(1-\alpha)}
 \tag{10.21}$$

The orness value whose OWA operator is described in the [0,1] interval is used to measure the importance of the HFLTS.

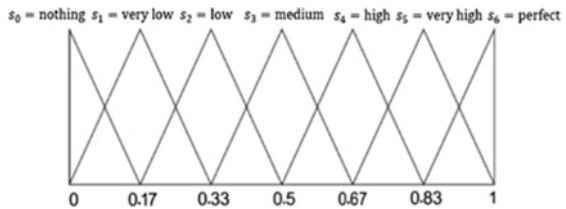
Stage 3. Sample fuzzy envelope

In this section, the transformation of a sample linguistic expression into a TFMF form is illustrated to clarify the fuzzy envelope. The linguistic term set, $S = \{s_0 = \textit{nothing}, s_1 = \textit{very low}, s_2 = \textit{low}, s_3 = \textit{medium}, s_4 = \textit{high}, s_5 = \textit{very high}, s_6 = \textit{absolute}\}$ is used in the sample application and its graphical representations is as follows (Fig. 10.5):

The following process steps are as follows:

- a. The comparative linguistic evaluation is defined by the context-free grammar form: *between low and high*.
- b. Linguistic evaluation is converted into HFLTS as $E_{G_H}(\textit{between low and high}) = \{s_2, s_3, s_4\}$.
- c. The set of aggregation elements of the HFLTS is defined: $T = \{a_L^2, a_R^1, a_M^2, a_L^3, a_R^2, a_M^3, a_L^4, a_R^3, a_M^4, a_R^4\}$.
 where $a_R^1 = a_M^2 = a_L^3, a_R^2 = a_M^3 = a_L^4$, and $a_R^3 = a_M^4$, so set T can be simplified as $T = \{a_L^2, a_M^2, a_M^3, a_M^4, a_R^4\}$.

Fig. 10.5 Graphical representation of a sample linguistic term set S



d. The parameters of the TFMF, $env_F(H_{s_4}) = T(a_4, b_4, c_4, d_4)$, are calculated as:

$$\begin{aligned}
 a_4 &= \min\{a_L^2, a_M^2, a_M^3, a_M^4, a_R^4\} = a_L^2 = 0.17 \text{ and} \\
 d_4 &= \max\{a_L^2, a_M^2, a_M^3, a_M^4, a_R^4\} = a_R^4 = 0.83 \\
 b_4 &= OWA_{W^2}(a_M^2, a_M^3) \text{ and } c_4 = OWA_{W^1}(a_M^3, a_M^4)
 \end{aligned}$$

while $i = 2$ and $g = 6$, α is calculated as $\alpha = (g - (j - i))/(g - 1) = 0.8$ and OWA weights are defined as:

$$\begin{aligned}
 W^2 &= (w_1^1, w_2^1)^T = (0.8, 0.2)^T \text{ and } W^1 = (w_1^1, w_2^1)^T = (0.2, 0.8)^T \\
 b_4 &= a_M^2 * 0.2 + a_M^3 * 0.8 = 0.466 \text{ and } c_4 = a_M^2 * 0.2 + a_M^3 * 0.8 = 0.636
 \end{aligned}$$

e. TFMF of the fuzzy envelope of H_{s_4} , $env_F(H_{s_4})$ is defined: $T = (0.17, 0.466, 0.636, 0.83)$.

Step 4. Operation of HFCM

Linguistic evaluations of experts define the causal relationship between concepts in the HFCM model. The linguistic expressions are transformed into the crisp values in $[-1, 1]$ interval using defuzzification methods. Thus, the causal relationships between the concepts in the dynamic HFCM can be calculated, and the stable states of the concepts to be reached in the long term can be determined. The crisp values obtained by the defuzzification method express the causal relationship strength between the concepts (C_i, C_j) and are called directed weight (w_{ij}). The sign of the directed weight represents the directly related or inverse relationship among concepts. The weights of all causal relationships in HFCM are defined in the weight matrix (W) whose diagonal elements, w_{ii} are equal to zero because of absence of self-loop in model. Experts’ linguistic expressions can define the initial state of the concepts. New state value of the concept C_i at the time t time iteration is represented as A_i^t in the interval $[-1, 1]$. $A^t = [A_1^t, A_2^t, \dots, A_n^t]$ representation is also shows general state values for all concepts. The new state vector of a concept, C_i in the next iteration is measured as follows:

$$A_i^{t+1} = f\left(\sum_{j=1}^n w_{ij}A_j^t + A_j^t\right) \tag{10.22}$$

Threshold function operation is an essential step in the new state calculation process. The hyperbolic tangent function is chosen for this study among the most commonly used threshold functions (sign, trivalent, sigmoid, and hyperbolic tangent function). The hyperbolic tangent function is chosen because the $[-1, 1]$ values obtained after the threshold calculation are compatible with real-life problems.

$$f(x) = \tanh(\lambda x) = \frac{e^{\lambda x} - e^{-\lambda x}}{e^{\lambda x} + e^{-\lambda x}} \quad (10.23)$$

The value of the lambda ($\lambda > 0$) constant, which shapes the slope of the hyperbolic tangent function, is predefined by researchers according to their research characteristics (Bueno and Salmeron 2009). The calculation of the causal relationship in the HFCM model is terminated when the difference between the two consecutive iteration values of all concept relationship values is less than 0.0001 (i.e., $A^{t+1} - A^t \leq 0.0001$), and the last state reached is defined as the “steady state”.

10.5 Application: Solar Energy Price Modelling with Hesitant Fuzzy Cognitive Map

The increasing importance of energy in life affects and is influenced by economic, social and environmental factors. The pricing of solar energy that is a developing member of the energy sector is shaped under similar factorial circumstances. The definition of causal relations among the main factors that determine solar energy prices is defined by the opinions and evaluations of experts under uncertainty and unpredictability conditions. Experts of this study is both the academic and energy-business community. Experts selected from the academic community are preferred because of their studies on economic analysis and decision making of renewable energies. The experts selected from the energy sector consist of analysts and specialists who make installation assessments of large-scale renewable and solar energy systems. Since the renewable energy pricing mechanisms are similar each other, the experts in renewable sector are consulted in assessing the factors that determine the solar energy price. Under these conditions, the HFCM model is used to describe the causal relationships among factors and the initial states of the factors around the solar energy price. The initial states of the factors are randomly developed, and different scenarios are defined. The scenarios are operated on the HFCM model, and the solar energy price and other factors’ reactions are observed during the model.

10.5.1 Determining of Weight Matrix and Initial State Vector

Firstly, the causal relationship between the factors and the powers of the causal relations among them must be defined for the operating the HFCM model. The “solar energy price” -based model is defined by twenty different models and the direction and sign of the causal relationship between the factors is determined by the collective opinion of experts (Fig. 10.6). The orange causality represents the

inverse proportion (that is, the value of a factor increases while the value of the other factor that is related decreases) and the blue causality represents the direct proportion (that is, the value of a factor increases while the value of the other factor that is related increases).

The HFCM consists of twenty-four factors, three of which are transmitters (GT, EE, ESE), eighteen of which are ordinary, and no receiver factor (Fig. 10.6). The highest in-degree factor is the SEP (Solar Energy Price) that is also the center of the model structure, and the highest out-degree factor is SLL (Supportive Law and Legislations). The highest centrality factor is SLL with twelve value and followed by SEP and EP (Energy Price).

The causal relationship between the factors of the model that is shaped around the solar energy price factor is determined by the academic and sectoral specialists in the field of solar energy and solar economics. Experts make evaluations based on hesitant linguistic terms to express causal relationships among factors more realistically and explicitly. Linguistic term set $S = \{s_0 : \text{nothing}, s_1 : \text{very low}, s_2 : \text{low}, s_3 : \text{medium}, s_4 : \text{high}, s_5 : \text{very high}, s_6 : \text{absolute}\}$ is used to generate linguistic assessments based on the context free grammar. The relationship matrix, which is defined linguistically by the common view of experts, is shown in Table 10.1. Expressions of linguistic evaluation are shown in abbreviation on Table 10.1. The “+” sign indicates a positive relationship, and the “-” sign indicates a negative relationship. Explanations of other abbreviations are as follows; btw: between, atl: at least, gth: greater than, lth: lower than, atm: at most, n: neighter, vl: very low, low:l, m: medium, h: high, vh: very high, and a: absolute. Linguistic expressions that describe the causal relationship between the factors are transformed into HFLTS using conversion functions (Table 10.2).

HFLTSs transformed from linguistic evaluations are converted into a trapezoidal fuzzy membership function $A \sim = (a, b, c, d)$ (Table 10.3). The intermediate b and c parameters of the trapezoidal fuzzy membership function are calculated using the OWA aggregation operator at this stage. The linguistic expressions converted to numerical values by the trapezoidal fuzzy membership function are transformed

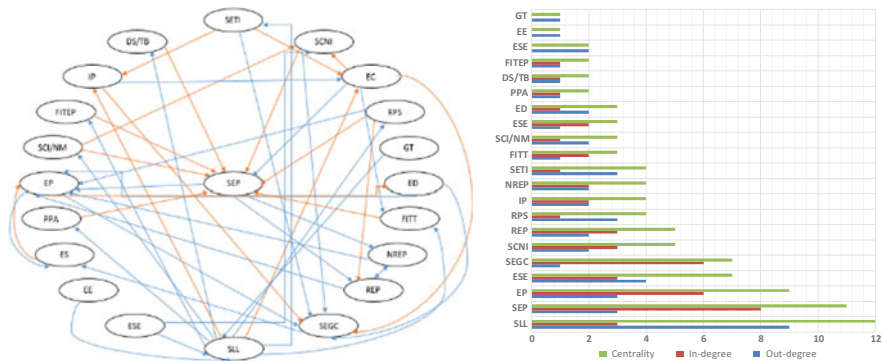


Fig. 10.6 Solar energy price centered HFCM and the values of the model structure metrics

Table 10.1 Experts' shared views on the causal relationships among the factors

	RPS	PPA	FITT	SCNI	DS/TB	ESE	FITEP	IP	SCI/NM	EP	
RPS										+atm_l	
PPA											
FITT											
SCNI											
DS/TB											
ESE			+btw_lvh	-atm_m							
FITEP											
IP					+atm_h						
SCI/NM				-btw_vlm							
EP											
REP										+gth_m	
NREP										+gth_l	
SLL	+at_l_m	+gth_m	+lth_h		+atm_m	-btw_lh	+lth_h	-btw_vlm	+lth_h		
EE											
ESE				+lth_m							
SEP										+gth_m	
ESE										-at_l_h	
ED										-btw_ma	
SEGC											
GT											
SETI						-atm_h		-gth_m			
	REP	NREP	SLL	EE	ESE	SEP	ESE	ED	SEGC	GT	SETI
RPS	-atm_m					-atm_m					
PPA						-btw_vlm					

(continued)

Table 10.1 (continued)

	REP	NREP	SLL	EE	ESE	SEP	ESE	ED	SEGC	GT	SETI
FITT						-ism					
SCNI						-gth_vl			+lth_h		
DS/TB						-btw_vlh					
ESE						+gth_m			-ish		
FITEP						-atl_m					
IP									-atm_m		
SCI/NM											
EP						-lth_l					
REP							+lth_h	-gth_h	+btw_vlm		
NREP	+lth_h	+gth_l									
SLL											+lth_m
EE			+atl_h								
ESE			+gth_vh								
SEP	+btw_lm	+atm_m									
ESE											
ED									+gth_vl		
SEGC							+btw_lm				
GT			+atm_h								
SETI									+lth_l		

Table 10.2 HFLTS transformation of experts' linguistic evaluations

	RPS	PPA	FITT	SCNI	DS/TB	ESE	FITEP	IP	SCI/NM	EP
RPS										{+} {n,v,l,l}
PPA										
FITT										
SCNI										
DS/TB										
ESE			{+} {l,m,h, vh}	{-} {n,v,l, l,m}						
FITEP										
IP						{+} {n,v,l,l, m,h}				
SCI/NM				{+} {v,l,l, m}						
EP										
REP										{+} {h,vh, a}
NREP										{+} {m,h, vh,a}
SLL	{+} {m,h, vh,a}	{+} {h, vh,a}	{+} {n,v,l,l, m}		{+} {n,v,l, l,m}	{-} {l,m,h}	{+} {n,v,l, l,m}	{-} {v,l,l, m}	{+} {h, vh,a}	
EE										
ESE				{+} {n,v,l, l}						
SEP										{+} {h,vh, a}

(continued)

Table 10.2 (continued)

REP	NREP	SLL	EE	ESE	SEP	ESE	ED	SEGC	GT	SETI
{+}{n,v,l,l,m}										
										{+}{n,v,l,l}
		{+}{h,vh,a}								
		{+}{vh,a}								
{+}{l,m}	{+}{n,v,l,l,m}									
								{+}{l,m,h,vh,a}		
						{+}{l,m}				
		{+}{n,v,l,l,m,h}								
								{+}{n,v,l}		

Table 10.3 Trapezoidal representation of HFLTS

	RPS	PPA	FITT	SCNI	DS/TB	ESE	FITEP	IP	SC/NM	EP
RPS	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,15,0,5)
PPA	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
FITT	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
SCNI	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
DS/TB	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
ESE	(0,0,0,0)	(0,0,0,0)	(0,17,0,44,0,77,1)	(0,0,-0,36,-0,67)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
FITEP	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
IP	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,59,0,83)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
SCI/ NM	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,-0,3,-0,47,-0,67)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
EP	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
REP	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,5,0,86,1,1)
NREP	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,33,0,65,1,1)
SLL	(0,33,0,65,1,1)	(0,5,0,86,1,1)	(0,0,0,36,0,67)	(0,0,0,0)	(0,0,0,36,0,67)	(-0,17,-0,47,-0,64,-0,83)	(0,0,0,36,0,67)	(0,-0,3,-0,47,-0,67)	(0,0,0,36,0,67)	(0,0,0,0)
EE	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
ESE	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,15,0,5)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
SEP	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,5,0,86,1,1)
ESE	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(-0,5,-0,86,-1,-1)
ED	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(-0,33,-0,61,-0,94,-1)
SEGC	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
GT	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)
SETI	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,0,0)	(0,0,-0,59,-0,83)	(0,0,0,0)	(-0,5,-0,86,-1,-1)	(0,0,0,0)	(0,0,0,0)

Table 10.3 (continued)

	REP	NREP	SLL	EE	ESE	SEP	ESE	ED	SEGC	GT	SETI
RPS	(0.0,-0.36,-0.67)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,-0.36,-0.67)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
PPA	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0,-0.3,-0.47,-0.67)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
FITT	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(-0.33,-0.5,-0.5,-0.67)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
SCNI	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(-0.17,-0.42,-1,-1)	(0.0,0.0)	(0.0,0.0)	(0.0,0.36,0.67)	(0.0,0.0)	(0.0,0.0)
DS/TB	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0,-0.27,-0.61,-0.83)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
ESE	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.5,0.86,1.1)	(0.0,0.0)	(0.0,0.0)	(-0.5,-0.67,-0.67,0.83)	(0.0,0.0)	(0.0,0.0)
FITEP	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(-0.33,-0.65,-1,-1)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
IP	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,-0.6,-0.67)	(0.0,0.0)	(0.0,0.0)
SCI/	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,-0.03,-0.33)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
NM											
EP	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.36,0.67)	(-0.67,-0.98,-1,-1)	(0.0,0.47,0.67)	(0.0,0.0)	(0.0,0.0)
REP	(0.0,0.0)	(0.33,0.65,1.1)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
NREP	(0.0,0.36,0.67)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
SLL	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
EE	(0.0,0.0)	(0.0,0.0)	(0.5,0.86,1.1)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
ESE	(0.0,0.0)	(0.0,0.0)	(0.83,1.1,1)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
SEP	(0.17,0.33,0.5,0.67)	(0.0,0.36,0.67)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
ESE	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
ED	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.17,0.42,1.1)	(0.0,0.0)	(0.0,0.0)
SEGC	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.17,0.33,0.5,0.67)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
GT	(0.0,0.0)	(0.0,0.0)	(0.0,0.59,0.83)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)
SETI	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.0)	(0.0,0.03,0.33)	(0.0,0.0)	(0.0,0.0)

into crisp values using the weighted average method to obtain computation values. The causal relations between the factors in the HFCM model are expressed by a single numerical value in the range $[-1,1]$ by defuzzification of the trapezoidal representations (Table 10.4). This obtained table is defined as the weight matrix of HFCM and expresses the causal relationship between the factors.

Since the initial states of the factors cannot be expressed with definite values within the dynamic energy system, the initial states of the factors are linguistically defined by the experts. The combination of different initial states of the factors reveals different solar energy price centered scenarios. The process steps followed in obtaining the weight matrix are also followed when the initial state table is obtained. Defuzzified trapezoidal fuzzy membership functions give crisp valued at the initial state scenarios. Applications are made on two scenarios (Case1, Case2) selected from ten cases developed by experts.

Equation (10.22) based on the initial states of the factors (A^0) and the weight matrix of HFCM (W) is run to obtain the next state vector A^1 . The equation that calculates the next state vector A^{t+1} from the previous state vector A^t is repeated until the state vector reaches the steady state, A^l . It is a common practice to terminate the iteration if the difference is less than 0.001 for each factor in the two consecutive state vectors ($A^{t+1} - A^t \leq 0.001$). In the application section, the hyperbolic tangent function (Eq. 10.23), which derives values in the range $[-1,1]$, is used as a threshold function and the value of lambda is assumed to be 0.7 ($\lambda = 0.7$).

10.5.2 Case Studies Base on Solar Energy Price

The two initial state vectors selected from the scenarios identified by the experts' joint evaluations are evaluated in this section. The values in the initial state are defined in the range $[-1,1]$, and the value of the corresponding factor reflects the current state of the solar energy price in the HFCM model. The positive (negative) value means that the factor has increased (decreased), while the zero value means that the factor has not changed. The changes in the initial state values of the factors over time and the convergence values of the factors are graphically displayed throughout the iterations. The number of iterations and the steady-state values of the factors change for each scenario. The order of the factors in the initial state vector is: Renewable Portfolio Standard (RPS), Power Purchasing Agreements (PPA), FIT with Tender (FITT), Self-consumption (non-incentivized) (SCNI), Direct Subsidies or Tax Breaks (DS/TB), Economic Components (EC), FIT for Entire Production (FITEP), Infrastructure Problems (IP), Self-consumption or Net-metering (incentivized) (SCI/NM), Energy Price (EP), Renewable Energy Price (REP), Non-renewable Energy Price (NREP), Supportive Law and Legislations (SLL), Environmental Effects (EE), Eco-social Effects (ESE), Solar Energy Price (SEP),

Table 10.4 Weight matrix of solar energy price HFCM model

	RPS	PPA	FITT	SCNI	DS/TB	ESE	FItep	IP	SCI/NM	EP	
RPS	0	0	0	0	0	0	0	0	0	0.132593	
PPA	0	0	0	0	0	0	0	0	0	0	
FITT	0	0	0	0	0	0	0	0	0	0	
SCNI	0	0	0	0	0	0	0	0	0	0	
DS/TB	0	0	0	0	0	0	0	0	0	0	
ESE	0	0	0.594	-0.23	0	0	0	0	0	0	
FItep	0	0	0	0	0	0	0	0	0	0	
IP	0	0	0	0	0	0.334	0	0	0	0	
SCI/NM	0	0	0	-0.366	0	0	0	0	0	0	
EP	0	0	0	0	0	0	0	0	0	0	
REP	0	0	0	0	0	0	0	0	0	0.867	
NREP	0	0	0	0	0	0	0	0	0	0.77	
SLL	0.770	0.867	0.23	0	0.23	-0.534	0.23	-0.366	0.23	0	
EE	0	0	0	0	0	0	0	0	0	0	
ESE	0	0	0	0.133	0	0	0	0	0	0	
SEP	0	0	0	0	0	0	0	0	0	0.867	
ESE	0	0	0	0	0	0	0	0	0	-0.867	
ED	0	0	0	0	0	0	0	0	0	-0.733	
SEGC	0	0	0	0	0	0	0	0	0	0	
GT	0	0	0	0	0	0	0	0	0	0	
SETI	0	0	0	0	0	-0.334	0	-0.867	0	0	
REP		NREP	SLL	EE	ESE	SEP	ESE	ED	SEGC	GT	SETI
-0.22958	0	0	0	0	0	-0.23	0	0	0	0	0
0	0	0	0	0	0	-0.366	0	0	0	0	0

(continued)

Table 10.4 (continued)

REP	NREP	SLL	EE	ESE	SEP	ESE	ED	SEGC	GT	SETI
0	0	0	0	0	-0.5	0	0	0	0	0
0	0	0	0	0	-0.666	0	0	0.23	0	0
0	0	0	0	0	-0.428	0	0	0	0	0
0	0	0	0	0	0.867	0	0	-0.668	0	0
0	0	0	0	0	-0.77	0	0	0	0	0
0	0	0	0	0	0	0	0	-0.23	0	0
0	0	0	0	0	-0.064	0	0	0	0	0
0	0	0	0	0	0	0.23	-0.936	0.366	0	0
0	0.77	0	0	0	0	0	0	0	0	0
0.23	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0.133
0	0	0.867	0	0	0	0	0	0	0	0
0	0	0.972	0	0	0	0	0	0	0	0
0.417	0.23	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0.666	0	0
0	0	0	0	0	0	0.417	0	0	0	0
0	0	0.334	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0.064	0	0

Energy supply (ES), Energy Demand (ED), Solar Energy Generation Capacity (SEGC), Global Treaties (GT), Solar Energy Technological Improvement (SETI).

Case1:

In this scenario, different initial states of the factors that affect the solar energy price are examined. The scenario analyzes the long-term effects of increasing and decreasing states of factors on solar energy price and other factors. Initial state vector is defined as $A_1^0 = [0.332 \ -0.972 \ 0.332 \ 0.168 \ -0.668 \ 0.972 \ 0.028 \ -0.5 \ 0.028 \ -0.168 \ 0.832 \ 0.972 \ 0.972 \ 0.668 \ 0.168 \ 0.028 \ -0.168 \ 0.168 \ 0.028 \ 0.5 \ 0.028]$. According to the scenario, the EC, NREL, SLL and REP factors appear with the highest increase of 0.972 in the initial state of the system. The increase in investment costs leads to an increase in renewable and non-renewable energy costs and energy prices. Laws and regulations that increase solar energy production capacity arise in order to balance high energy production prices. The scenario also includes high environmental sensitivity and high international agreement impacts with the other high positive values. The factors that decrease in the initial state are EP, ES, IP, DS / TB, and PPA factors and the greatest reduction is seen in DS / TB and PPA factors supporting solar energy production capacity. Other remaining factors have a weak impact on the system with their low growth rates.

The simulated solar energy price-centered HFCM model simulated under the defined initial state reaches equilibrium state after 45 iterations. In the equilibrium model (Fig. 10.7), the final state vector of the factors is as follows: $A_1^l = [0 \ 0 \ -0.003 \ 0.001 \ 0 \ -0.001 \ 0 \ 0 \ 0 \ -0.862 \ -0.193 \ -0.337 \ 0 \ 0 \ 0 \ 0 \ -0.050 \ 0.813 \ 0.429 \ 0 \ 0]$. The steady-state values obtained by simulating the HFCM model are interpreted as follows:

- The system shows complex fluctuations in the first twelve iterations. After twelfth iteration, the tendencies of the factors begin to appear more clearly. Factors which direct to the converged values after forty-first iteration reaches to the final state values after forty-fifth iteration.
- The factors of RPS, PPA, DS/TB, FITEP, IP, SCI/NM, SLL, EE, ESE, SEP, GT, and SETI converge to zero in the balanced system. This state means that there is no enhancing or reducing effects on these factors. The solar energy price among these factors is also a constant value; there is no tendency to increase or decrease. The state of the solar energy price causes the general system factors to remain unchanged.
- In this scenario, ED, SEGC, and SCNI factors show an increasing tendency with 0.813, 0.429, and 0.001 values. The main reason for the high increase in energy demand is the decrease in renewable energy, non-renewable energy, and general energy prices. Increased energy demand is balanced by increasing solar energy production capacity. The installation of individual solar energy systems without incentive contributes to increasing solar energy capacity with a low increase.
- While the highest reductions are seen in EP, NREP, and REP factors (-0.862, -0.337, -0.193 respectively); ES, FITT, and EC factors affect the system with low reductions (-0.020, -0.003, -0.001 respectively). The inverse relationship

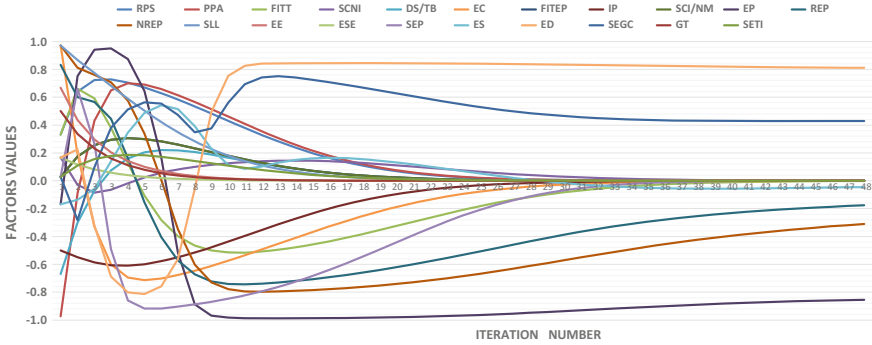


Fig. 10.7 HFCM simulation of Case1

between energy demand and energy prices is the leading cause of the decline in energy prices. The decline in energy prices is also triggered by reductions in renewable energy (excluding solar energy) and non-renewable energy prices. Reductions in support and incentives for solar energy generation may have led to a lower reduction in overall energy supply. The scale economy created by the developing solar energy systems technology leads to a reduction in installation costs, though there are no incentives for solar energy.

• **Case2:**

This scenario is designed to examine the effects of the supports and programs for improving solar energy systems on solar energy price and general system factors. Therefore, the system consists of supportive factors with increasing GT, FITT, PPA, SLL, DS/TB and RPS (0.972, 0.972, 0.972, 0.832, 0.668, 0.500, 0.168) and decreasing EC and IP (-0.028, -0.500). Nevertheless, there are some mitigating factors to increase the solar energy capacity and reduce the solar energy price in the system such as FITEP, ESE, SETI, SCNI, and SCI/NM (-0.168, -0.668, -0.668, -0.832, -0.832). The solar energy price, solar energy generation capacity, demand for energy, energy supply, and other supportive factors tend to increase in this scenario. Initial state vector is defined as $A_2^0 = [-0.972 \ 0.5 \ 0.028 \ 0.332 \ -0.668 \ 0.168 \ -0.832 \ 0.332 \ -0.332 \ -0.028 \ 0.972 \ 0.168 \ 0.832 \ 0.832 \ 0.168 \ -0.028 \ -0.668 \ -0.168 \ -0.332 \ 0.5 \ 0.332]$. The HFCM simulation model reaches to the equilibrium state at the 37th iteration and obtained steady state vector is as follows: $A_2^l = [0 \ 0 \ 0.004-0.001 \ 0 \ 0.001 \ 0 \ 0 \ 0-0.724 \ 0.007 \ 0.012 \ 0 \ 0 \ 0 \ 0.001 \ 0.047 \ 0.766 \ 0.451 \ 0 \ 0]$. The general behavior of the factors according to the graphical representation (Fig. 10.8) and the obtained values are summarized as follows.

- The highest tendency to increase is seen in the energy demand (0.766) that is resulted from the high reduction in energy price (-0.724). The high decline in energy prices in the initial state and the increase in solar energy production support will lead to an increase in energy supply and cause energy prices to continue at low levels over the long run. The second highest increase is seen in

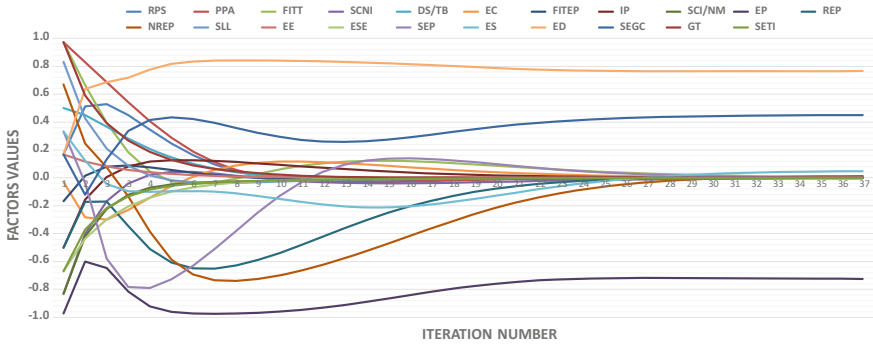


Fig. 10.8 HFCM simulation of Case2

solar energy generation capacity (0.451) which is the result of the focus of this scenario that includes the high increase in solar energy support. The increase in solar energy capacity provides a low level of energy supply (0.047) and causes the installation costs to increase (EC, 0.001). The increase in the installation costs of solar energy systems can lead to an increase in the bid prices for the FIT (0.004) and solar energy prices. The high increase in energy demand also leads to renewable (including solar energy, 0.007) and non-renewable energy prices (0.012).

- When the system reaches equilibrium, the factors of IP, GT, EE, ESE, SLL, SETI, DS / TB and FITEP go into inertia position, and the steady-state values of these factors are indicated by zero. The inertia of most of the policies that support the development of solar energy systems proves that the system can stand independently as unsupported and uncontrolled. The inertia results show that the widespread of solar energy use has removed environmental, economic and social problems, has stopped national and international concerns, and has led to the more balanced distribution of incentives.
- The establishment of individual solar energy systems (-0.001) and energy price (-0.724) factors show a decline in an equilibrium state. Solar energy capacity reaches satisfying with high support and encouragement, so support for the establishment of new systems is either eliminated or reduced. Increasing energy demand with energy price can be balanced by increasing solar energy generation capacity or raising the renewable or non-renewable energy prices.

The solar energy price HFCM model is evaluated through two different scenarios that are developed according to the initial state values of the factors. Scenario models reach equilibrium state with different iteration numbers, and model factors take different equilibrium state values according to their initial state values. The solar energy price reaches a constant equilibrium value at the end of calculations made with different initial state vectors. The inertia state of the solar energy price causes the factors supporting and disturbing the solar energy system to go into inertia state. The continuation of the equilibrium energy model by energy supply,

energy demand, and energy price factors shows that solar energy price is evaluated within renewable and non-renewable energy prices. The solar energy generation capacity increase occurs depending on energy demand in market conditions without any incentive mechanism.

10.6 Conclusion

In this chapter, the causal relationships among the solar-energy price factors are identified. The economic, environmental and social conditions and the uncertainties are considered in the model. This HFCM model is used for identifying and assessing relationships among factors accurately. The causal relationships among the factors are determined by linguistic evaluation depending on the experts' knowledge, skills, and experience. Since the initial states of the factors cannot be measured, the initial state values of factors are determined by the knowledge of the experts. The linguistic expressions used in determining the causal relationships between the factors and the initial state value of the factors are transformed into the HFLTS and the trapezoidal fuzzy membership function. The weight matrix and the initial state vector are obtained by defuzzification of the TFMF and they are used to simulate the HFCM model. The simulated HFCM models result in different equilibrium state values for the factors. For example, the energy price reaches -0.862 in the first scenario and solar energy generation capacity converges 0.451 in the second scenario.

Similar results are obtained in the equilibrium states of the HFCM models that are developed at the solar energy price cantered. Although the initial state vectors are different, the solar energy price does not tend to increase or decrease at the end of the simulations. The inertia state of the solar energy price causes the factors directly affecting the solar energy system to go into an inertia state for each scenario. The energy model, which continues its existence by energy supply, energy demand, and energy price factors, accommodates solar energy price in renewable and non-renewable energy prices. Also, equilibrium situations show that the development of new solar power generation systems takes place in market conditions without any incentive mechanism.

In the future studies, the applied HFCM model-based pricing studies can be extended for other renewable energy sources since the renewable energy sector has similar pricing structure to solar energy. Thus, renewable energy price prediction models can be improved by considering the factors affecting renewable energy price and their impact levels on pricing. As a result, more accurate energy price estimation can be made with a more realistic price estimates of renewable energies, which will have significant shares in meeting future energy demand.

References

- Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, 20(1), 87–96.
- BP. (2017). Statistical Review of World Energy June 2017; 66 [cited 2017 10 December]. Available from: <https://www.bp.com/content/dam/bp/en/corporate/pdf/energy-economics/statistical-review-2017/bp-statistical-review-of-world-energy-2017-full-report.pdf>.
- Bloomberg New Energy Finance. (2015). New Energy Outlook [cited 2017 10 December]. Available from: https://data.bloomberglp.com/bnef/sites/4/2015/06/BNEF-NEO2015_Executive-summary.pdf.
- Bordogna, G., & Pasi, G. (1993). A fuzzy linguistic approach generalizing boolean information retrieval: A model and its evaluation. *Journal of the American Society for Information Science*, 44(2), 70.
- Bueno, S., & Salmeron, J. L. (2009). Benchmarking main activation functions in fuzzy cognitive maps. *Expert Systems with Applications*, 36(3), 5221–5229.
- Çoban, V., & Onar, S. Ç. (2017). Modelling solar energy usage with fuzzy cognitive maps. In *Intelligence Systems in Environmental Management: Theory and Applications* (pp. 159–187). Springer.
- Conkling, R. L. (2011). *Energy pricing: Economics and principles*. Berlin: Springer Science & Business Media.
- Crawley, G. M. (2016). *Solar energy*. Hackensack, NJ: World Scientific Publishing Co., Pte. Ltd.
- Delgado, M., et al. (1998). Combining numerical and linguistic information in group decision making. *Information Sciences*, 107(1–4), 177–194.
- Filev, D., & Yager, R. R. (1998). On the issue of obtaining OWA operator weights. *Fuzzy Sets and Systems*, 94(2), 157–169.
- International Energy Agency (IEA). (2016). Trends 2016 in Photovoltaic Applications [cited 2017 22 December]. Available from: http://iea-pvps.org/fileadmin/dam/public/report/national/Trends_2016_-_mr.pdf.
- Jaimol, T., Ashok, S., & Jose, T. (2011). Hybrid pricing strategy for solar energy. *Proc. Sustainable Energy and Intelligent Systems (SEISCON)*, Chennai, July 2011, pp. 121–125.
- Kahraman, C., Kaymak, U., & Yazici, A. (2016). Fuzzy logic in its 50th year: New developments, directions and challenges (Vol. 341). Berlin: Springer.
- Kosko, B. (1986). Fuzzy cognitive maps. *International Journal of Man-Machine Studies*, 24(1), 65–75.
- Kosko, B. (1997). *Fuzzy engineering*. New Jersey: Prentice Hall.
- Liu, H., & Rodríguez, R. M. (2014). A fuzzy envelope for hesitant fuzzy linguistic term set and its application to multicriteria decision making. *Information Sciences*, 258, 220–238.
- MDAI. (2014). M.D.f.A.I. A few aggregation operators 2014. Available from: <http://www.mdai.cat/ifao/operadors/index.php?llengua=en>.
- Michael, G. (2010). *Fuzzy cognitive maps: Advances in theory, methodologies, tools and applications. Studies in fuzziness and soft computing* (Vol. 10, pp. 978–3). Berlin: Springer.
- Ministry. (2017). E.a.N.R Renewable Energy Resources Support Mechanism (YEKDEM) [cited 2017 20 November]. Available from: <http://www.eie.gov.tr/yenilenebilir/YEKDEM.aspx>.
- Mir-Artigues, P., & Del Río, P. (2016). *The Economics and Policy of Solar Photovoltaic Generation*. Cham: Springer.
- Mizumoto, M., & Tanaka, K. (1976). Some properties of fuzzy sets of type 2. *Information and Control*, 31(4), 312–340.
- Papageorgiou, E. I. (2013). *Fuzzy cognitive maps for applied sciences and engineering: from fundamentals to extensions and learning algorithms* (Vol. 54). Heidelberg: Springer Science & Business Media.
- PV-Magazine. (2017). Turkey adds 553 MW of solar in H1 2017. [cited 2017 10 November]. Available from: <https://www.pv-magazine.com/2017/09/11/turkey-adds-553-mw-of-solar-in-h1-2017/>.

- Rodriguez, R. M., Martinez, L., & Herrera, F. (2012). Hesitant fuzzy linguistic term sets for decision making. *IEEE Transactions on Fuzzy Systems*, 20(1), 109–119.
- Ruspini, E. H. (1969). A new approach to clustering. *Information and Control*, 15(1), 22–32.
- Scientists. (2015). U.o.C Increase Renewable Energy [cited 2017 10 November]. Available from: http://www.ucsusa.org/clean_energy/smart-energy-solutions/increase-renewables/real-energy-solutions-the.html#.WhualTeZk2x.
- Stern, N. (2015). *Why are we waiting? The logic, urgency, and promise of tackling climate change*. Cambridge, MA: Mit Press.
- The National Academies of Sciences, E., and Medicine. (2009). G8+5 Academies' joint statement: Climate change and the transformation of energy technologies for a low carbon future [cited 2017 12 December]. Available from: <http://www.nationalacademies.org/includes/G8+5energy-climate09.pdf>.
- Timilsina, G. R., Kurdgelashvili, L., & Narbel, P. A. (2012). Solar energy: Markets, economics and policies. *Renewable and Sustainable Energy Reviews*, 16(1), 449–465.
- Torra, V. (2010). Hesitant fuzzy sets. *International Journal of Intelligent Systems*, 25(6), 529–539.
- World Energy Council. (2016) World Energy Resources [cited 2017 10 December]. Available from: <https://www.worldenergy.org/publications/2016/world-energy-resources-2016/>.
- Yager, R. R. (1988). On ordered weighted averaging aggregation operators in multicriteria decisionmaking. *IEEE Transactions on systems, Man, and Cybernetics*, 18(1), 183–190.
- Yager, R. R. (1993). Aggregating fuzzy sets represented by belief structures. *Journal of Intelligent & Fuzzy Systems*, 1(3), 215–224.
- Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning—I. *Information Sciences*, 8(3), 199–249.
- Zadeh, L. A. (1996). *Fuzzy sets, in fuzzy sets, fuzzy logic, and fuzzy systems: Selected papers by Lotfi A Zadeh* (pp. 394–432). River Edge, NJ: World Scientific.
- Zatzman, G. M. (2012). *Sustainable energy pricing: Nature, sustainable engineering, and the science of energy pricing*. Hoboken, NJ: Wiley.