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ORIGINAL ARTICLE

Modeling renewable energy usage with hesitant Fuzzy cognitive map

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Abstract Renewable energy sources (solar, wind, tidal, etc.), which are unlimited and have a fair distribution in the world, are an alternative to the depleting fossil fuels (coil, petroleum, natural gas, etc.). It is necessary to identify the right technologies and methods to make more effective use of renewable energy sources including uncertainty and irregularity in resource creation. In this study, dynamic environmental factors affecting the production of solar and wind energy are defined and the relations among them are linguistically expressed by the experts. These linguistic relationships among factors and their initial states are assessed by new developed hesitant linguistic cognitive map method that is an extension of hesitant fuzzy sets and fuzzy cognitive map. Relational development between factors was observed by simulating the model according to the initial condition of the factors. Thus, the model helps investors and governments to direct their solar and wind energy investment decisions.

Keywords Hesitant fuzzy cognitive map · Renewable energy · Solar energy · Fuzzy sets

Introduction

The energy obtained from infinite natural sources such as wind power, hydropower, solar energy, geothermal energy, biomass, tidal power and wave power are called renewable energy. In the last two decades, renewable energy has become a serious energy source. Between the years 1990 and 2014, total renewable electricity generation enlarged by 191% [1]. Europe's 28% of overall electricity generation is obtained from renewable energy in 2014 [1]. Although hydropower plants have the highest renewable energy generation capacity, wind and solar power generation capacities are significantly increasing in the recent years. Figure 1 shows the share of energy from renewable sources in gross final consumption of energy in 2011.

Among the renewable energy sources, solar power has the highest increase capacity. In 2014, solar power generation capacity increased by 14.1% compared with 2013 [1]. Although there is a significant increase in the installed capacity of solar energy sources, the percentage of solar energy in the total installed capacity is still limited. Understanding and modeling the solar energy capacity can enhance the solar energy production. The factors and the relations among the solar energy generation are uncertain, complex and vague. Fuzzy cognitive maps are excellent tools for dealing with complexity and ambiguity inherent in modeling problems [2]. Hesitant fuzzy sets are the extensions of fuzzy sets where more than one membership value of an element can be defined [3,4]. Hesitant fuzzy sets and hesitant linguistic term sets enable better expressing the experts' evaluations [4–6]. In this study, hesitant fuzzy cognitive maps are used for modeling solar energy generation capacity.

In general, this study examines the dynamic behavior of factors whose behavior is unclear during the installation phase of renewable energy systems. In this way, the relationships between the factors are determined linguistically by expert opinions and the behavior of the factors and the general system can be observed. This model can be differentiated according to the opinions of experts which vary according to economic, social, political and environmental conditions.

The rest of the paper is organized as follows: In Sect. "Fuzzy cognitive map", preliminaries for fuzzy cognitive

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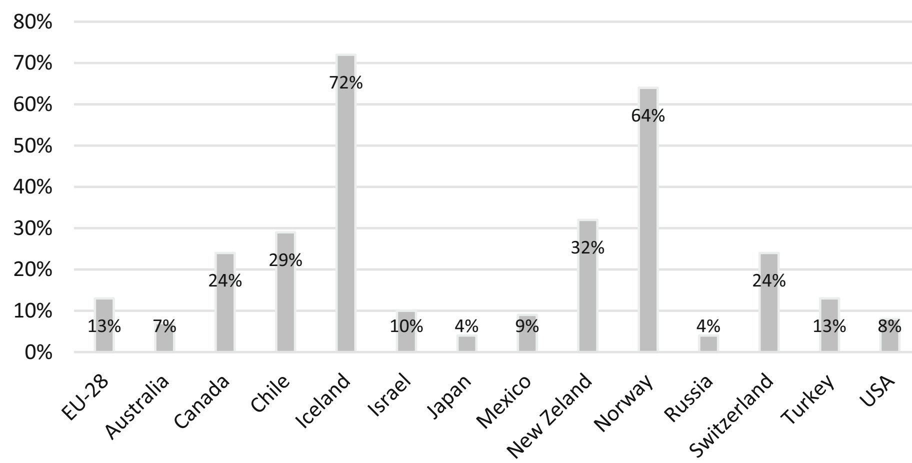
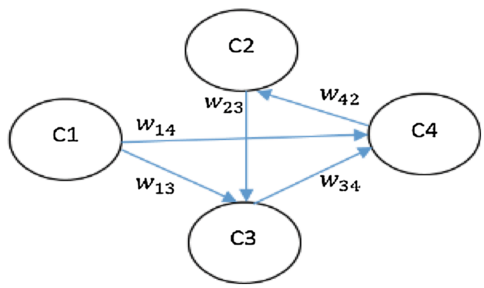


Fig. 1 The share of energy from renewable sources [1]



$$W = \begin{bmatrix} 0 & 0 & w_{13} & w_{14} \\ 0 & 0 & w_{23} & 0 \\ 0 & 0 & 0 & w_{34} \\ 0 & w_{42} & 0 & 0 \end{bmatrix}$$

Fig. 2 Graphical representation of FCM and its weighted matrix form

maps are given. Section "Hesitant Fuzzy cognitive map (HFCM)" introduces the hesitant fuzzy cognitive maps (HFCMs). In Sect. "Modeling renewable energy usage based on HFCMs", the proposed hesitant fuzzy renewable energy cognitive map with different scenarios is given. In the last section, conclusions and further suggestions are given.

Fuzzy cognitive map

Fuzzy cognitive map (FCM) which is an extension and combination of the cognitive map [5] and fuzzy logic [6,7] was introduced by Kosko [8]. Direct or indirect causal and fuzzy (non-binary) relationships between concepts are represented in the FCM. Fuzzy causal relations among concepts are generated by consulting the experts or general literature reviews. The fuzziness of these sources stems from the uncertain, complex and dynamic environments and decision factors in it [9,10]. FCM can be shown in a symbolical form with concepts or factors (nodes) and connections or causal relationships (arcs/edges). Connections represent the interactive causality among concepts that it reflects the dynamic relationships in systems. Edges that are shown with a directed arrows are weighted using signed fuzzy values in the interval $[-1, 1]$ [8,11].

Concepts (factors) and causal relationships among them can be modeled as a map for a visual expression of a system whose parts are schematically showed with nodes (C_i) and weighted edges (w_{ij}) where are represented with three states as $w_{ij} < 0$ negative causality, $w_{ij} > 0$ positive causality, and $w_{ij} = 0$ no relation. The sign of the causal relationship causes an increase or decrease in the activation level of a concept within each iteration.

Concepts do not influence itself, which means there is no self-loop in the model. The visual expression of the model can be transformed into a mathematical form as an adjacency matrix which indicates the relationships among nodes with fuzzy values. These fuzzy values represent the weights of the relationships and the initial weights of all interactive combinations among the nodes in FCM are shown with a weight matrix (W) which is a $n\,x\,n$ matrix and whose diagonal values are zero $(w_{ii} = 0)$ due to no self-loops. A sample FCM is drawn with four concepts (C_1, C_2, C_3, C_4) and five directed and weighted edges is shown in Fig. 2.

Time-dependent states of concepts in the FCM are described with an activation level $\left(A_i^t\right)$ which represents the presence of a related concept in the system using [0, 1] interval values. The activation levels of all concepts of the FCM in time t is shown in a state vector as $A^t = \left[A_1^t, A_2^t, \ldots, A_n^t\right]$ and the initial state vector is symbolized as A^0.

Initial state values of concepts and weight values of connections are defined by experts' assessments or literature reviews that also represent the scholars' assessments in written form [12]. These fuzzy evaluations become starting points for FCM operations and new state values of concepts are calculated with consecutive iterations [13] as follows:

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

According to Eq. (1) for concept i, C_i, total causal effects of other concepts on the C_i is calculated by time-dependent iterative operations and using threshold function, $f(.)$, which transforms the new state values in the [0, 1] or [−1, 1] intervals that change according to threshold function type. A_i^{t+1} represents the new state values of concept C_i at time $t+1$ after the first iteration from time t.

Although there are commonly used four different threshold functions that are bivalent, trivalent, sigmoid, and hyperbolic functions, sigmoid and hyperbolic threshold functions which are continuous transformation functions and have an ability to transform the iterative state values into the fuzzy representation form in the [0, 1] or [−1, 1] interval are frequently used in FCM studies.

- Sigmoid function (Eq. 2) is a continuous transformation function and are used to transform the sum of the weights and state values in the [0, 1] interval. This property provides it to be commonly used in the FCMs.

$$f(x) = \frac{1}{1+e^{-\delta x}} \quad (2)$$

- Hyperbolic tangent function (Eq. 3) is also a continuous transformation function (sigmoid-shaped function) and transforms the sum of the weights and state values in the [−1, 1] interval. By this way, inverse relations between concepts and negative state values can obviously be observed and interpreted in FCMs.

$$f(x) = \tan\mathrm{h}(\delta x) = \frac{e^{\delta x} - e^{-\delta x}}{e^{\delta x} + e^{-\delta x}} \quad (3)$$

where e is the Euler number and δ is the positive parameter ($\delta > 0$) that draws the function curve. x is the activation level of a concept at related time (sum of weighted state values and activation level of the previous time). After these threshold operations, new state values and activation level are obtained that they are convenient to fuzzy form.

Delta (δ) is a previously defined constant value that determines the shape of the function such as large delta values ($\delta \geq 10$) produce discrete functions and small values ($0 < \delta \leq 1$) produce linear functions. Specific delta values can be defined for each different study such that it should be fit with the study content and also reflect the researchers' findings obviously [11].

Iteration process for activation levels is updated until to the converged steady-state values that are measured based on the limit value. Limit values can be defined based on the iteration number or the difference between last two state values such as $A^{t+1} - A^t \leq f$ (general acceptance is $f = 0.001$).

FCM is an important analyzing and decision-making tool that has an ability to obviously reflects the complex, dynamic, and uncertain real-world problems visually and matrix form. Causal relationships among concepts in the FCM can be observed and made an inference for a long-term circumstances. The realistic and simple tool in the analyzing and decision-making of the uncertain real-world problems. Therefore, FCMs have been applied in many different scientific fields such as strategic planning [14], environmental management [15], and decision-making [16].

Hesitant fuzzy cognitive map (HFCM)

Evaluations in real-world conditions do not only base on numbers such that they also expressed with the linguistic assessments (natural language) such as words and sentences [6]. Linguistic evaluation expressions (high, medium, low) that are shaped by personal perceptions, knowledge, and experience cannot give an exact assessment of numbers and they include uncertainty and hesitancy. However, these evaluations are highly fit to human nature such that people can easily express themselves and naturally judge in the decision states.

But it appears that linguistic terms also include the hesitancy in the evaluation processes where experts cannot directly define their opinions by only using one assessment word such as low, very high, medium. Torra [4] proposed a solution step for this problem by defining "Hesitant Fuzzy Sets (HFSs)" that explain the set of values for a membership of a single element and enable experts to comment on the concepts and relationships among them.

The hesitant fuzzy linguistic term sets (HFLTS) presented as an extension of HFSs by Rodriguez et al. [17] reveals as an ordered finite subset of the consecutive linguistic term set. Experts overcome their challenges about hesitancy among several linguistic values using HFLTS that is an ordered finite subset of consecutive linguistic terms of linguistic term sets [17]. For example, a sample HFLTS $H_s = \{s_2: \text{low}, s_3: \text{medium}, s_4: \text{high}\}$ can be defined using linguistic term set $S = \{\text{nothing, very low, low, medium, high, very high, perfect}\}$. Basic mathematical operations and notations of HFLTS based on the linguistic term set S can be shown as follows [17]:

- The bounds and complement of the HFLTS, H_s;

  Upper bound $H_{S^+} = \max(s_i) = s_j, s_i \in H_s$ and $s_i \leq s_j \quad \forall_i$;
  Lower bound $H_{S^-} = \min(s_i) = s_j, s_i \in H_s$ and $s_i \geq s_j \forall_i$;

- The basic operations of the HFLTSs (H_s, H_s^1, H_s^2) that are complement, union and intersection;

$$H_s^c = S - H_s = \{s_i | s_i \in S \quad and \quad s_i \text{ not } \in H_s\}$$
$$\text{and } \left(H_s^c\right)^c = H_s$$
$$H_s^1 \cup H_s^2 = \{s_i | s_i \in H_s^1 \quad \text{or} \quad s_i \in H_s^2\}$$
$$H_s^1 \cap H_s^2 = \{s_i | s_i \in H_s^1 \quad \text{and} \quad s_i \in H_s^2\}.$$

New values that are obtained after these basic operations also will be a HFLTS.

Experts can comment on real-world problems and events using comparative linguistic expressions. These type hesitant linguistic expressions and linguistic terms in a natural language can be generated using context-free grammar that is shown as G_H. A context-free grammar G_H is defined based on the 4-tuple (V_N, V_T, I, P), where V_N is the set of non-terminal symbols such as primary term, composite term; V_T is the set of terminal symbols such greater than, lower than; I is the starting symbol and an element of V_N; and the production rules, P are defined based on the extension of the Backus–Naur form [17].

For example, "at least medium", "greater than low", "lower than high", and "between low and very high" hesitant linguistic expressions are described by context-free grammar, G_H . Linguistic expressions are more flexible and natural for experts to evaluate the hesitant circumstances.

Linguistic expression defined according to context-free grammar should be transformed into the HFLTS by transformation functions E_{G_H}, [17]. These transformation processes provide to use the linguistic expressions in the computation and evaluation processes. For example

- $E_{G_H}(s_i) = \{s_i | s_i \in S\}$
- $E_{G_H}(at\ most\ s_i) = \left\{s_j | s_j \in S\ and\ s_j \leq s_i\right\}$
- $E_{G_H}(at\ least\ s_i) = \left\{s_j | s_j \in S\ and\ s_j \geq s_i\right\}$
- $E_{G_H}(lower\ than\ s_i) = \left\{s_j | s_j \in S\ and\ s_j < s_i\right\}$
- $E_{G_H}(greater\ than\ s_i) = \left\{s_j | s_j \in S\ and\ s_j > s_i\right\}$
- $E_{G_H}\left(between\ s_i\ and\ s_j\right) = \left\{s_k | s_k \in S\ and\ s_i \leq s_k \leq s_j\right\}$

where $S = \{s_0: nothing, s_1: very\ low, s_2: low, s_3: medium, s_4: high, s_5: very\ high, s_6: absolute\}$ is the linguistic terms set.

For example, according to linguistic term set *S*={*nothing, very low, low, medium, high, very high, perfect*}, is the transformation of linguistic expressions "at least medium", "greater than high" and "between medium and very high" into HFLTS can be shown as :

- $E_{G_H}(at\ least\ medium) = \{medium, high, very\ high, absolute\}$
- $E_{G_H}(greater\ than\ high) = \{very\ high,\ absolute\}$
- $E_{G_H}(between\ medium\ and\ very\ high) = \{medium,\ high,\ very\ high\}.$

The set of information is aggregated to obtain a unique datum using aggregation operators such as mean, arithmetic mean, weighted arithmetic mean, and OWA operator [18] that are as follows:

$$Arithmetic\ mean\ (a_1, a_2, \ldots, a_n) = \sum_{i=1}^{n} \frac{a_i}{n} \tag{4}$$

$$Weighted\ mean\ (a_1, a_2, \ldots, a_n) = \sum_{i=1}^{n} w_i * a_i \tag{5}$$

where w_i is the weight of i-th information source (w_i).

$$\text{Ordered Weighted Averaging (OWA)}\ (a_1, a_2, \ldots, a_n) = \sum_{i=1}^{n} w_i * b_i \tag{6}$$

where b_i is the i-th largest element of the aggregated objects $a_1, a_2, \ldots, a_n$ and their permutation values are ordered from the largest to the lowest. w_i is the element of the aggregated weight vector $W = (w_1, w_2, \ldots, w_3)^T$ and represents the weight of the ordered i-th data in the interval [0, 1]. All weights in W that can be measured by different ways such as average, max, and min are aggregated using summation formulation as $\sum_{i=1}^{n} w_i = 1$ [15].

To represent the optimism and pessimistic degree of the OWA operator, the orness method is used [15] as:

$$orness\ (W) = \frac{1}{n-1} \sum_{i=1}^{n} w_i * (n - i) \tag{7}$$

where orness value is positive and smaller than 1 where it is defined as optimistic OWA operator that closes to one and defined as pessimistic OWA operators that close to zero [19].

The OWA operator has been widely used aggregation operator in computational intelligence, especially fuzzy logic, with its ability to aggregate and model the linguistic expressions. OWA aggregation operator is used to aggregate the fuzzy membership functions of the linguistic terms of the HFLTS and the trapezoidal fuzzy membership function is obtained for the fuzzy envelope [18,20]. OWA weights that are used in OWA operation reflect the differentiation of the importance of the linguistic terms that it proceeds from the hesitation among linguistic expressions.

HFLTSs obtained by transformation of linguistic term sets are easily compared and computed by enveloping method which developed by Rodríguez et al. [21]. HFLTS is described using envelope method within linguistic interval whose upper and lower bounds are shown as (H_{S^+}) and

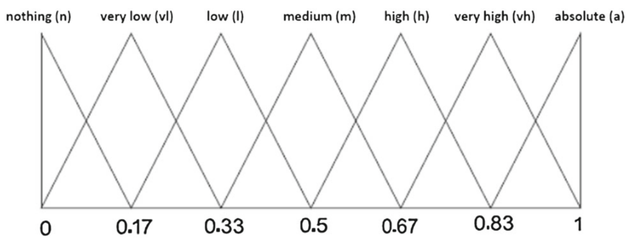


Fig. 3 The linguistic term set $S = \{s_1, s_2, \ldots, s_6\}$

(H_{S^-}), respectively. Envelope of HFLTS, $env\,(H_S)$, is represented as within these bounds as follow:

$$env\,(H_S) = \left[H_{S^-}, H_{S^+}\right], \quad H_{S^-} \leq H_{S^+}. \tag{8}$$

For instance, HFLTS, $H_s = \{medium, high,\ very\,high\}$ that is the linguistic expression of "between medium and very high" is enveloped as $env\,(H_S) = [medium,\ very\,high]$ where linguistic term sets is $S = \{nothing, very\,low, low, medium, high, very\,high, absolute\}$.

HFLTS is aggregated with using OWA aggregation operator based on fuzzy membership functions of the linguistic terms and obtained a new HFLTS to achieve a fuzzy envelope of HFLTS [18,22].

The trapezoidal fuzzy membership function is accepted as a useful tool for defining and representing the weights of the causal relationships among factors. These causal relations can be defined by linguistic values that involve the uncertainty and hesitancy and can be transformed to the fuzzy numbers by representing triangular, trapezoidal, sigmoid, and Gaussian functions [23].

Trapezoidal fuzzy membership function, $\tilde{A} = (a, b, c, d)$, is used in this study to define the fuzzy envelope of the HFLTS whose values are transformed from linguistic terms (Fig. 3).

After these core knowledge and definitions, the HFCM operation flow process (Fig. 4) can be summarized as following steps:

Step 1 HFCM consists of concepts and weighted edges among concepts that can be defined by experts with their linguistic expressions. A context-free grammar is used to generate the linguistic evaluations such as at highest, between very low and medium, and lower than very high.
Step 2 Linguistic evaluations that define the causal relations among concepts are transformed to HFLTS according to the linguistic term set.
Step 3 A trapezoidal fuzzy membership function is obtained by aggregating the fuzzy membership functions of the linguistic terms of the HFLTS.
Step 4 Trapezoidal fuzzy membership functions are transformed within the $[-1, 1]$ interval by weighted average defuzzification method and adjacency matrix of the concepts is accepted as a weight matrix (W) of the HFCM.
Step 5 Initial state vector of the concepts and iterated in the activation function for each time step.

Activation levels in the related time calculated under the hyperbolic tangent threshold function until the state value of each concept converges to its steady state equilibrium.

HFCM (Fig. 5) utilizes the hesitant fuzzy linguistic terms sets (HFLTS) that experts can easily and freely express their hesitant and uncertain judgments on the relationships between the factors. HFCM is more realistic and flexible than the traditional fuzzy cognitive maps because of its ability to reflect experts' knowledge and experiences that are expressed by hesitant linguistic values.

Modeling renewable energy usage based on HFCMs

The energy that is generated from natural sources such as sun, wind, wave, and geothermal is called the renewable energy. Although there are many alternative renewable

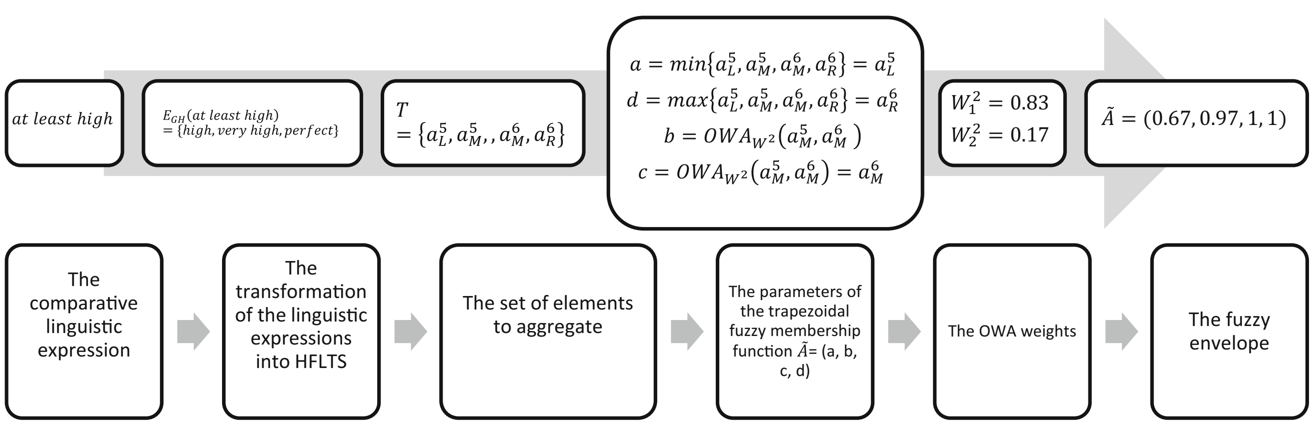
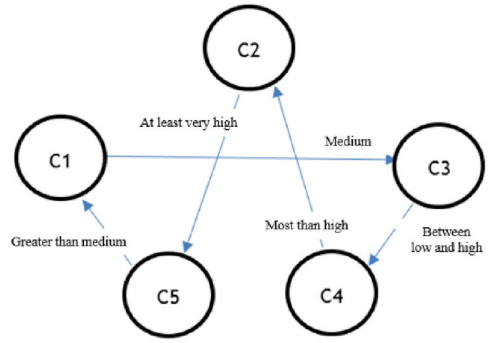


Fig. 4 Sample fuzzy envelope generation process

Fig. 5 A sample HFCM and HFLTS matrix



	C1	C2	C3	C4	C5
C1	-	-	{medium}	-	-
C2	-	-	-	-	{very high, perfect}
C3	-	-	-	{low, medium, high}	-
C4	-	{very high, perfect}	-	-	-
C5	{high, very high, perfect}	-	-	-	-

energy sources, only some of them are available for investors because of their constrained conditions such as regulation, incentive, costs, and energy demand. In this study, the factors that affect and/ or are affected by generated solar and wind energy capacities will be defined and the causal relationships among them will be observed in HFCM. In this way, basic reasons (factors) that affect the solar and wind generated energy capacities will be able to define and the new perspectives and visions will be provided to investors for their long-term investments.

In this study, the model is defined and the causal relationships are designed based on solar and wind energy generation. Solar (SEGC) and the wind (WEGC) energy generated capacity are basic factors in the energy generation system and refer the total amount of energy that is produced from new constituted solar and wind energy systems.

Cost of solar (COSE)/wind (COWE) energy, technological applicability for solar (TASE)/wind (TAWE) energy and solar (SEI)/wind (WEI) energy incentive factors directly affect the amount of newly generated solar and wind energy capacities and also have indirect effects on other global factors. The cost of energy systems refers the total amount of cost that stem from investment cost, production, transmission and distribution costs. Technological applicability for energy systems represents the applicability of solar and wind energy technologies under the given geological, physical, and operational conditions for generation and distribution of the solar and wind energy. Other auxiliary factors around the solar and wind energy generations are an incentive and any type of governmental supports that encourage users and investors to direct the solar and wind energy usage and investments. Solar and wind energy incentive are monetary (e.g., zero-interest loan, tax relief, feed-in-tariff) or non-monetary (e.g., law, regulation, policies) encouragement programs whose special purposes are to increase the use of solar and wind energy-efficient equipment and reduce non-renewable energy usage.

The remaining factors in the model that are renewable energy regulation (RER), energy demand (ED), energy price (EP), and energy supply (ES) can be defined as common factors because they have global impacts on the model. Renewable energy regulation reflects the state policies either to support the green energies or to continue to use the fossil-based energy sources. These policies will have important causal and direct effects on the solar and wind energy incentive and other related factors. Energy demand represents a number of energy requirements of the people to maintain their daily activities such as heating, transportation, cooking, and production. Energy price is the amount of payment for energy which is used or will be used from conventional or renewable sources. Energy supply meets the total amount of energy which will be produced by all types of energy sources in the future. Figure 6 represents the concepts and causal relationships among them such that positive relationships are showed with solid lines and negative relationships are showed with dotted lines. Different scenarios are simulated to observe the impact of possible changes and steady state of the system after the iteration process in HFCM. The following procedures are followed in each of these scenarios.

First of all, experts express their evaluations about the relationships among concepts with linguistic statements (Table 1). The effects of a factor on the other factors were expressed as "negative" or "positive" and the degree of the effect using comparative linguistic expressions such as positive at least high and negative between medium and very high. For example, causal relationship between *wind energy incentive* and *cost of wind energy* was linguistically defined as *negative greater than high* in Table 1.

These linguistic expressions are transformed into HFLTS that are used to obtain the trapezoidal fuzzy membership functions using OWA operations. Trapezoidal fuzzy membership functions are defuzzified with the weighted average method and transformed into numeric values as weight matrix (Table 2) and initial state vectors. The activation levels of the concepts in time t and a state vector of the HFCM model is iterated under the threshold function until the HFCM reaches its steady state equilibrium.

In this section, general and specific movements of the system are observed according to the possible scenarios. In the

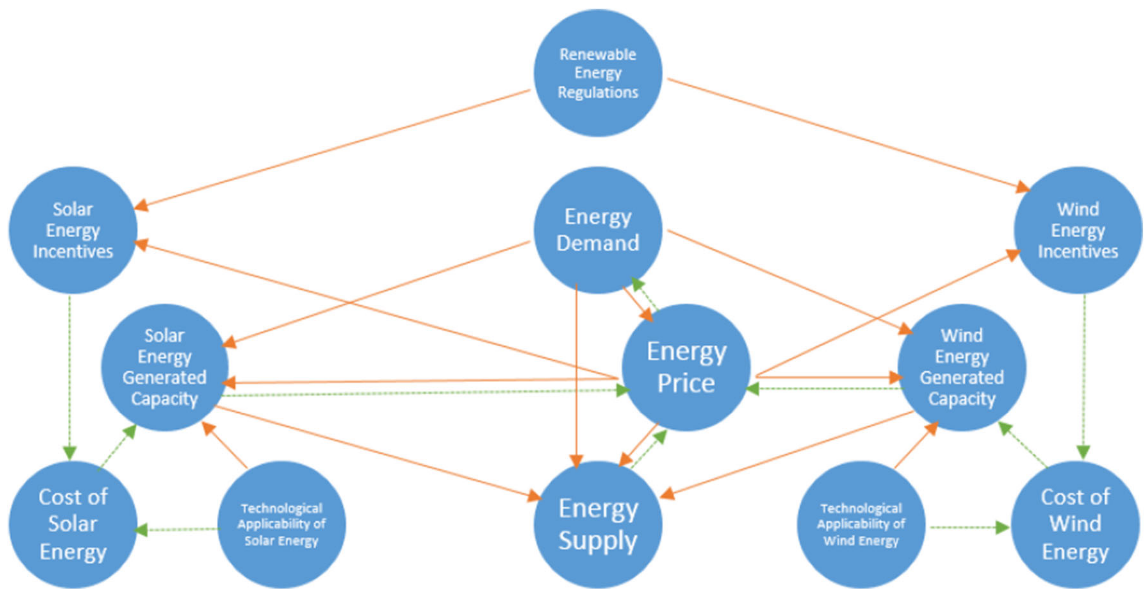


Fig. 6 Graphical representation of the relational HFCM

long run, the convergence of the factors to the values and the interactions among the factors are defined. Example applications for possible situations are as follows:

(a) *An example for the existence of one concept in model*
In this scenario, *renewable energy regulation* factor is activated which means governments increase their interest in developing renewable energies and support their usage and investments. Other concepts are accepted as a stable in the initial state of the system that means there is no direct impact on their current status. Initial state vector is represented as $A^0 = [0\,0\,0\,0\,0\,0\,0\,0\,0\,1\,0\,0\,0]$ and changes of the concepts and their converged values are observed in the iteration process. The results of the simulation for sample case (Fig. 7) can be listed as follow:

1. First reactions seem as increase evenly of the solar and wind energy incentive that are directly affected by renewable energy regulation. Increasing effects in the energy incentive cause to reduce the interest of the governments in the renewable energies to regulate the general energy supply and prices in their countries.
2. Increasing incentive in the solar and wind energy cause to reduce their costs and increase their investments and new generated capacities. So far, no change is observed in the energy price, energy supply, and energy demand because of long path lengths among these concepts that it causes long reaction time. Afterward, increasing solar and wind energy capacities raise energy supply and reduce energy prices that cause to increase energy consumption and energy demand at the low rates. At these periods, causal interactions among concepts increase and rapid changes can be observed for their rates in the dynamic system.
3. Renewable energy regulation does not cause any change in the technological applicability of the solar and wind energy during the iteration process because of their closed form and transmitter properties that mean they are not affected by any other factors in the system.
4. Renewable energy regulation loses its influence in the medium term and reaches zero steady value. This circumstance causes to decrease of the incentive and decrease of the decay rate of the cost of solar and wind energies. As a domino effect, new solar and wind energy generation capacities and energy supply start to decrease that it causes to the increase of the energy price and the decrease in the energy demand. Concepts except for technical applicability for solar and wind energy reflect fluctuating motions as decrease and increase. At the final state in the convergence zone, they reach to the zero steady values that mean there will be no change in their state.

(b) *An example for a combination of concepts in model*
The scenario is planned in which the *cost of solar and wind energy* systems are reduced by improvement in the solar and wind energy technologies and increasing research and development investments. Also, the scenario includes the decrease of the *renewable energy regulation* that reflects the disinterest of the government on the green energy and increase of the *technical applicability of solar and wind energy* at the same period. By this scenario, transmitter concepts that are *renewable energy regulation, the technical ability of solar and wind energy* are included in the system at the same time. Initial state vector of the scenario is defined as $A^0 = [0\ -1\,1\,0\,0\ -1\,1\,0\,1\,0\,0\,0]$ and their time dependent changes are observed in the iteration process.

Table 1 Linguistic relationship matrix

	SEGC	COSE	TASE	SEI	WEGC	COWE	TAWE	WEI	RER	ED	EP	ES
SEGC											Negative between I m	Positive between vI I
COSE	Negative at least vh											
TASE	Positive between h a	Negative greater than h										
SEI		Negative greater than vh										
WEGC											Negative between I m	Positive between I h
COWE					Negative atleast vh						Negative between I m	Positive between I h
TAWE					Positive between h a	Negative greater than vh						
WEI						Negative greater than h						
RER				Positive greater than h				Positive greater than h				
ED	Positive at least vh				Positive at least vh						Positive between m h	Positive at least h
EP	Positive between h vh			Positive lower than m	Positive between h vh			Positive lower than m		Negati ve lower than m		Positive at least h
ES											Negative greater than h	

Table 2 Weight matrix

	SEGC	COSE	TASE	SEI	WEGC	COWE	TAWE	WEI	RER	ED	EP	ES
SEGC	0	0	0	0	0	0	0	0	0	0	−0.138	0.057
COSE	−0.936	0	0	0	0	0	0	0	0	0	0	0
TASE	0.838	−0.936	0	0	0	0	0	0	0	0	0	0
SEI	0	−0.972	0	0	0	0	0	0	0	0	0	0
WEGC	0	0	0	0	0	0	0	0	0	0	−0.416	0.534
COWE	0	0	0	0	−0.936	0	0	0	0	0	0	0
TAWE	0	0	0	0	0.838	−0.972	0	0	0	0	0	0
WEI	0	0	0	0	0	−0.936	0	0	0	0	0	0
RER	0	0	0	0.936	0	0	0	0.936	0	0	0	0
ED	−0.936	0	0	0	0.936	0	0	0	0	0	0.583	0.867
EP	0.750	0	0	0.133	0.75	0	0	0.133	0	−0.133	0	0.867
ES	0	0	0	0	0	0	0	0	0	0	−0.602	0

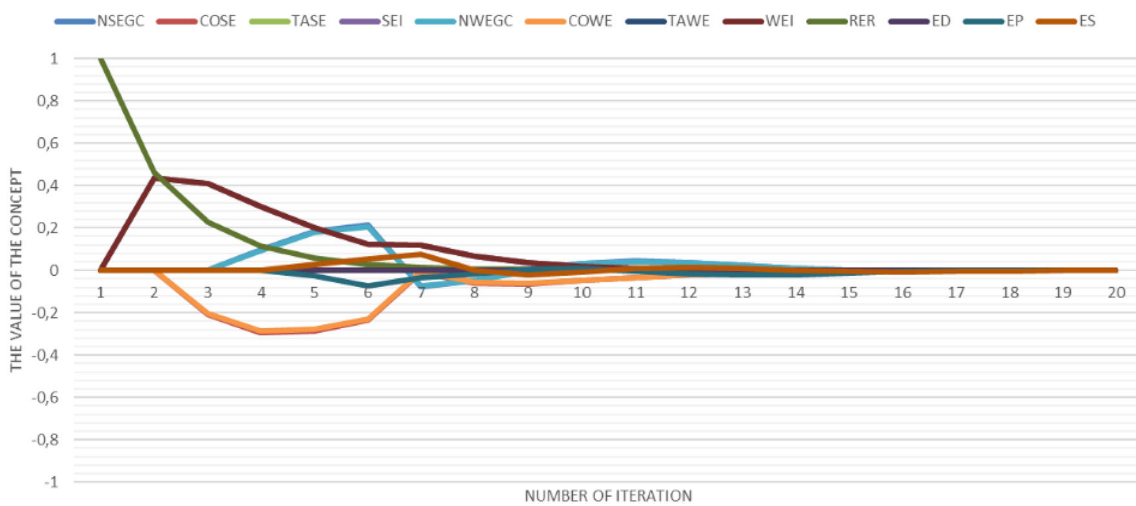


Fig. 7 The graphical result of the HFCM simulation for the existence of one concept in the model

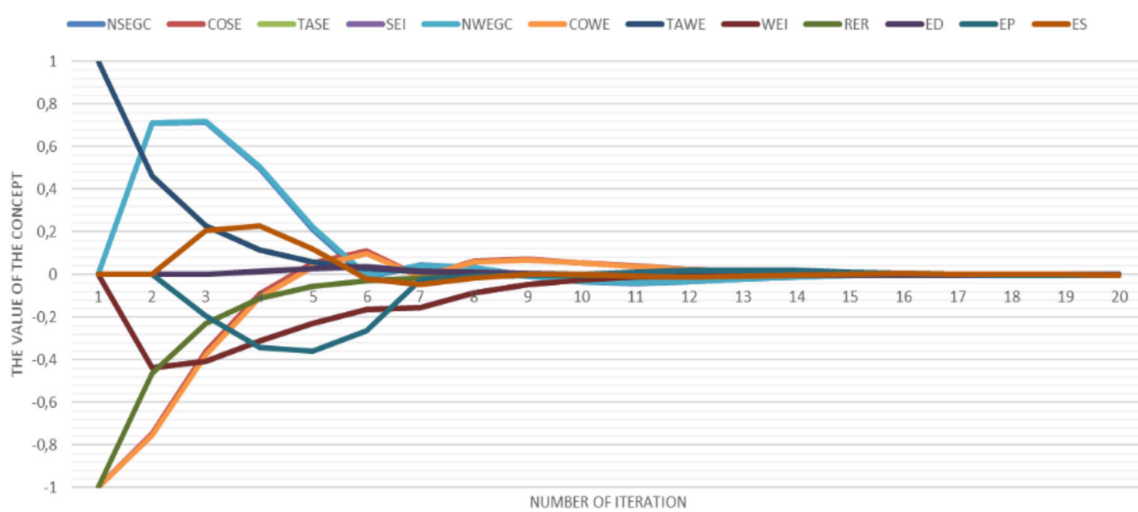


Fig. 8 Graphical result of the HFCM simulation for a combination of concepts

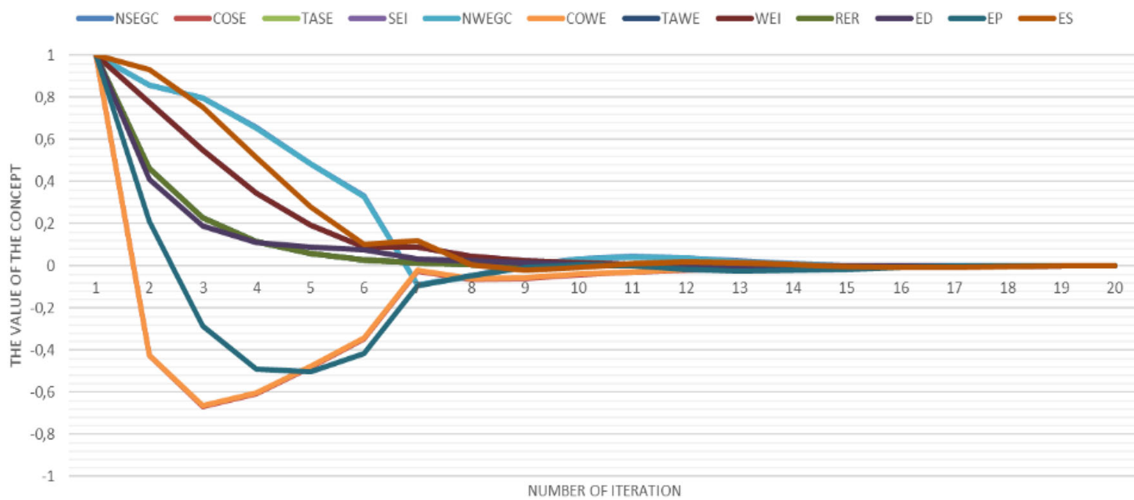


Fig. 9 Graphical result of the HFCM simulation for the existence of all concepts

The results of the simulation for sample case (Fig. 8) can be listed as follow:

1. First, new solar and wind energy generation capacities increase with high rates and solar and wind energy incentive starts to decrease and continue to decrease during the iteration process that it arises from disinterest of governments on green energy by decreasing renewable energy regulation. Initial active concepts do not protect their impacts whose values reduce in the first reaction. No change is observed in the energy demand, energy supply, and energy price because of their global properties and long path lengths with active concepts.
2. Increasing solar and wind energy generation capacities cause the increase of energy supply and reduce of the energy price that also increases the energy consumption and energy demand. Increase in the cost of solar and wind energy in the medium period cause the decrease of the newly generated solar and wind energy capacities and the energy supply. This energy bottleneck indicates that energy price will rise and energy demand will reduce in the same period. Energy supply, demand and price and new solar and wind energy generation capacities factors converge to steady state at zero value in small fluctuations.
3. Active factors in the initial state lose their effects on the other factors during the iteration process. Decreasing investments and new generation capacities of the solar and wind energies stimulate governments to take precaution for supporting these concepts by regulation and incentive. Also, decreasing cost of solar and wind energy systems are balanced by incentive and general energy demand and prices. Technical applicability for solar and wind energy are limited by solar and wind energy systems, so their positive active initial values decrease and reach steady states at zero values.
4. At this scenario, all concepts get involved in the model as active and they causally interact with each other. All concepts, except technical applicability of solar and wind energy that decrease along iterations, increase and decrease during the iteration process and converge to zero values at the steady state.

(c) *An example for the existence of all concepts in model* System is modeled based on the positive availability of all concepts and their initial states are defined as $A^0 = [1111111111]$. Although all concepts are positively existence in the model, system include some opposite interacts among concepts such as increase of the cost of systems will cause to decrease of the new generation capacities of the solar and wind energy system. The solar and wind energy generation-based model reaches steady state at zero level which means system is at the balance and there will be no change in the long term. Results of the model can be listed as follows (Fig. 9):

1. The cost of solar and wind energy factors changes their signs from positive to negative at the first reaction that it stems from increasing supporting policies such as incentive and regulation. Cost reductions and increasing incentive in solar and wind energy systems cause increases in new capacity of solar and wind energy and energy supply and decreases in energy price that will stimulate the energy consumption in the short term. Technical applicability for solar and wind energy decrease during the iterations and reach the steady state in the medium term that it arises from technical limitations such as infrastructure, distance from energy grids, technical knowledge and new investments. Generally, concepts in

the model rapidly decline and converge to their steady state to balance the system by causal reactions.

2. Increasing energy price is reduced by increasing solar and wind energy capacities that are supported by incentive and regulation which surpass increasing cost factors for solar and wind generations. When incentive and regulation lose their impacts on the cost of solar and wind energies at the medium period, newly generated energy capacities of solar and wind systems decrease in a few iterations but then they recover their increasing state. This state stems from increasing solar and wind energy capacities that cause the increase in energy demand and reduce of energy price and profits such that model reacts to balance the system by decreasing supports (incentive and regulation) on solar and wind energies.
3. All concepts in the system converge to steady state at the zero level after 20 iterations. The steady state of the solar and wind energy generation system reflects the balance of model that means any concepts will not change their state in the long term. Energy supply and energy price concepts are lastly converged to their steady values because of their long decaying times resulting from long path lengths.

Conclusion

Renewable energy is an important alternative to conventional energy whose sources are finite and becoming expensive in time. The tendency to the renewable energy increases the importance of the determining right energy generation technology in a dynamic environment. To deal with this kind of complex problems in the energy sector, we applied the new HFCMs model that is an extension of hesitant fuzzy sets and fuzzy cognitive map.

In this study, the causal relationships among concepts in solar and wind energy generation are described by linguistic term sets that help expert to express their evaluations with natural language. These linguistic terms are transformed into trapezoidal fuzzy membership functions using HFLTS and OWA operations. Trapezoidal fuzzy membership functions are defuzzified with the weighted average method and transformed to $[-1, 1]$ interval as a weight matrix. Weight matrix and the initial state of the factors are included the iteration process within hyperbolic tangent threshold function in Eq. (3) until convergence. Converge values represent the steady state of the factors in the model.

In the sample applications, three scenarios are designed according to the current situation of the solar and wind energy systems and verified the accuracy of the theoretical energy model and the usability of the new generated HFCM tool. Simulation processes show that incentive and regulation that refer the support and international obligation of governments have the most important impact on new solar and wind energy generation capacities. However, technical applicability for solar and wind systems that are transmitter factors have a less important impact on new green energy systems. Simulation results also show that the affecting and being affected of the transmitter (renewable energy regulations and technical applicability for solar and wind energy) and global concepts (energy demand, energy supply, and energy price) take a long time because of their long path lengths within concepts.

In the future research, solar and wind energy systems can be divided in their special fields and investigated their main factors using HFCM as modeling and simulation tool. Factors for new solar and wind energy generation systems can be extended by reviewing the literature or applying wide experts' knowledge that can be expressed using linguistic definitions. Also, future studies can include the improvement of FCM and HFCM simulation models that are useful tools to analyse real life systems and represent the linguistic expression of experts in the models.

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