An Interactive Multi-Criteria Decision-Making Framework between a Renewable Power Plant Planner and the Independent System Operator

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Abstract

Providing efficient support mechanisms for renewable energy promotion has drawn much attention from researchers in the recent years. The connection of a new renewable power plant to the transmission system has impacts on different electricity market indices since the other strategic generation units change their behaviour in the new multi-agent environment. In this paper, as the main contribution to the previous literature, a combination of multi-criteria decision-making approach and multi-agent modelling technique is developed to obtain the maximum possible profits for an intended renewable generation plan and also direct the investment to be located in a way to improve electricity market indices besides supporting renewable energy promotion. Fuzzy *Q*-learning electricity market modelling approach in combination with the technique for order preference by similarity (TOPSIS) is used as a new decision support system for promotion of renewable energy for the first time in the literature. The proposed interactive multi-criteria decision-making framework between the independent system operator (ISO) and the renewable power plant planner provides a win-win situation that improve market indices while help the renewable power plant planning. The effectiveness of the proposed method is examined on the IEEE 30-bus test system and the results are discussed.

Keywords: Electricity Market; Power System; Renewable Energy; Reinforcement Learning; Fuzzy *Q*-learning.

Nomenclature

A. Sets

Ω_B	Set of indices of buses.
Ω_D	Set of indices of demands.
$\Omega_{D.z}$	Set of indices of demands located in bus z.
Ω_G	Set of indices of generation units.
$\Omega_{G.z}$	Set of indices of generation units located in bus z.
Ω_S	Set of all states (different values of RPP output power)

B. Parameters

x_{mz}	Inductive reactance of the line connecting buses m and z.
c_i	Intercept of marginal benefit function of ith demand.
d_i	Slope of marginal benefit function of ith demand.
u_j	Intercept of jth generation unit's marginal cost function.
b_j	Slope of jth generation unit's marginal cost function.
$P_{mz}^{\max}$	Thermal/stability active power limit of the line connecting buses m and z.
T	Number of iterations in learning phase of multi-agent model.
N_G	Number of generation units.
N_B	Number of transmission system buses.

C. Variables

$P_{D.it}$	Active power consumption of ith demand in hour t.
$P_{G.jt}$	Active power production of jth generation unit in hour t.
$P_{L.mnt}$	Active power flow from bus m to bus n in hour t.
δ_{zt}	Voltage angle of bus z in hour t.
α_{jt}	Intercept of bid function of jth generation unit in hour t.
$LMP_{G.jt}$	Locational marginal price of the bus to which generation unit j is connected in hour t.

$LMP_{D.it}$	Locational marginal price of the bus to which ith demand is connected in hour t.
LMP_{nt}	Locational marginal price of nth bus in hour t.

1. Introduction

A. Motivation and Background

Battling with climate change by decreasing carbon emission has been considered as a serious agreement of governments across the globe in the Paris Climate Change conference at the end of 2015 in order to better reduce the global warming. For realizing this objective, undoubtedly, a shift in electricity generation paradigm from fossil fuels to the more environmental-friendly renewable generation is an obligation. This issue enforces countries to set their targets for increasing the share of renewable energy in the energy generation mix. As a vision for 2030, the contribution of renewable energy in electricity generation of European Union is set 27% [1]. This target would be 20% for China, and 12% for the United States [1]. Globally, the share of renewable energy in the total mix of generation is estimated to reach 45% in 2040 [2]. Considering these ambitious targets highlights the requirements for more attentions to the provision of motivations and support for the new renewable investment projects. There are some mechanisms that have been proposed and applied in different countries for renewable energy expansion. Giving attention to the stressful situation of power system around the world, a successful promotion mechanism needs to carefully consider power and energy market operation and planning issues. The importance of these considerations becomes better clarified by considering rapid world energy consumption that will increase 56% by 2040 according to Energy Industry Agency [3]. Considering power system and energy market issues in any promotion mechanism for renewable energy expansion emerges as an important research gap which needs to be addressed in new studies.

B. Relevant Background

In recent years, different renewable support mechanisms have been examined in different countries. Renewable portfolio standard and feed-in-tariff are recognized as the examples of the most popular supporting mechanisms [4-6]. Feed-in-tariff mechanism is a pricing policy which is realized by purchasing renewable energy at a guaranteed price while renewable portfolio standard is a quota system that enforces producers to consider a certain amount of renewable energy in their mix [7]. To the best of our knowledge, neither feed in tariff and renewable portfolio standard nor most of the other incentive mechanisms consider power system technical problems.

From another viewpoint, several studies were conducted to include power system technical considerations in renewable power generation expansion planning [8-15] in the recent years. These studies can be divided into two groups in terms of the size of the renewable units: i) bulk renewable generation plans, and ii) small-scale renewable plans. Some of the papers in the first category considered transmission expansion planning in coordination with renewable power generation expansion to support the set renewable energy target [8-10]. A few papers considered renewable generation expansion within the scope of conventional generation planning schemes [11, 12].

As for the latter, a few research tasks such as in [13-15] can be mentioned. Renewable generation expansion was modelled in a bi-level optimisation framework in [13] by considering demand response. In [14], a subsidy objective function as the pollution not emanated was proposed in a multi-objective optimisation model as an encouraging mechanism in the favour of small-scale renewable resource promotion.

In [15] an optimisation framework was proposed for renewable resources, energy storage, and distribution system expansion planning. To the best of our knowledge, none of the power system planning studies considered the effect of renewable investment on the strategic behaviour of the other market players [16]. This important gap affects directly the profit of the new renewable power generation plan and also the other electricity market indices which have influence totally on market operation.

In general, strategic behaviour of electricity market was modelled by equilibrium [17, 18] or agent-based approaches [19, 20]. As discussed in [20], due to the inherent intermittency of renewable generation resources, agent-based approaches are more preferable. In [19] a Least Squares Continuous Actor-Critic algorithm with a robust market clearing approach was deployed for day-ahead electricity market modelling in the presence of renewable generation.

In [20], output power of renewable resources was considered as the state in modelling of electricity market. Since fuzzy *Q*-learning approach has been successfully applied for dealing with continuous states in reinforcement learning, this approach was examined for electricity market modelling [20, 21]. Also, in [20], some electricity market indices such as Nash index, social welfare, and congestion cost were taken into consideration.

Since the mentioned indices reflect different attributes, it is necessary to utilize effective multi-criteria decision-making techniques. Recently, multi-criteria decision-making approaches have been successfully applied for evaluation of renewable power generation plans in different regions of the world [22-24].

In [22], analytical hierarchical process (AHP) was applied for estimating and ranking barriers of renewable energy development in Nepal. A hybrid decision-making trial and evaluation laboratory and analytic network process (DEMATEL-ANP) model was used for selecting alternative renewable energies in [23]. In [24], a new renewable energy source strategy was evaluated using a multi-criteria decision-making model by implementing hesitant fuzzy linguistic term set.

The technique for order of preference by similarity to ideal solution (TOPSIS) is one of the powerful multi-criteria decision-making techniques. Based on TOPSIS approach, the selected alternative has the shortest geometric distance from the positive ideal alternative and the longest geometric distance from the negative ideal alternative [25]. In the previous literature, TOPSIS has been used in congestion management of transmission system [26], evaluation of power generation plans [26], strategy selection in a game-based congestion management approach [27], and resiliency assessment [25]. As it is observed from these papers, there is a lack of enough research regarding the application of TOPSIS for location prioritization of renewable power plan which is discussed in this paper.

C.Content and Contributions

In this paper, we provide an interactive decision-making model between ISO and a renewable power plant planner to locate the intended renewable power generation plan while improving market indices. To this end, a combination of well-established reliable multi-criteria decision-making approach and multi-agent modelling technique is used to find the best locations in a transmission system for integration of a proposed renewable power generation plan by the investor's average payments and electricity market behavioural indices. Based on the proposed method, a proper incentive is determined to motivate the investors to select a location in which not only maximum average profit is achieved by the investor, but also maximum improvement is achieved for electricity market indices. The major contributions of the paper are listed as follows:

- Proposing a new interactive multi-criteria decision-making model for simultaneously supporting the proposed renewable power generation plans by providing them with an incentive to maximize their profits while gaining the most possible improvement in electricity market behavioural indices.
- Simulation of the effects of renewable energy plans on electricity market indices.
- Provision of a new decision support system by combination of multi-agent modelling and multi-criteria decision-making approaches.

For achieving the goals of this paper, we adopt fuzzy Q-learning approach that we proposed in [20] as an effective market modelling method in the presence of renewable power penetration. In the current paper, we use this approach for evaluating the behaviour of electricity market as well as obtaining the electricity market indices by integrating a proposed renewable energy plan. Also, TOPSIS approach is used as the employed multi-criteria decision-making technique. Various successful power system applications of TOPSIS could be referred to [26-28].

D. Organization

After having provided the introductory information in Section I, Section II describes the proposed methodology. This section is divided into *three* major parts. In the *first* part, market modelling through multi-agent fuzzy Q-learning is described and in the *second* part, 8 important market modelling indices are provided and finally in the *third* part TOPSIS is applied to rank the transmission nodes based on electricity market indices. In Section III, the proposed methodology is applied on a case study including IEEE 30-bus transmission system. Finally, Section IV concludes the paper.

2. Methodology

A renewable power plant planner intends to integrate a new renewable power producer (RPP) to the power system. The evaluation of the impact of the RPP on electricity market indices is depicted in the block diagram shown in Fig. 1.

The proposed evaluation system considers the investors' proposal for different capacities of RPP investment. Different candidate locations are considered based on the geographical aspects of the considered renewable resources, i.e. wind power plants. It is mentioned that the approach is flexible enough to consider any types of renewable resources.

The goal of this evaluation system is to assess and rank the candidate buses based on average RPP profit and electricity market indices to incentivize the renewable investor to install RPP with maximum possible profit while improving electricity market indices.

As the procedure shown in Fig. 1 demonstrates, the installation of RPP in each location is examined by means of a combination of multi-agent fuzzy Q-learning and TOPSIS approach as a decision-making tool for ranking-based simulation of electricity market behaviour in interaction by electricity market clearing model. The rest of this section elucidates the proposed procedure.

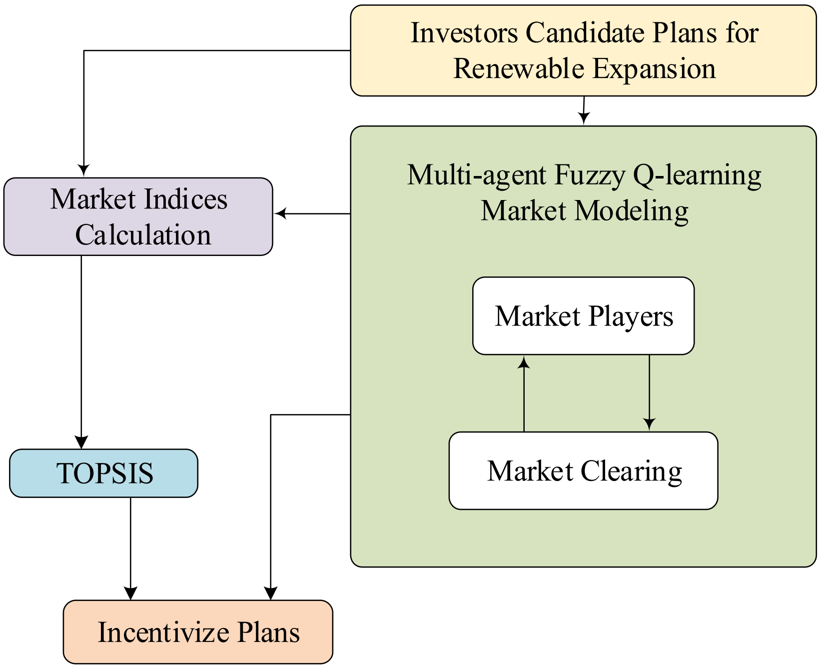

Fig. 1. *Overview of the proposed interactive multi-criteria decision-making framework.*

A. Multi-agent fuzzy Q-learning market modelling

In the proposed method, the agents or market players are conventional generation units. The strategic agents offer their bid to participate in market clearing procedure. The bid of each generation unit is a linear supply function ($\alpha_{jt} + b_j P_{G.jt}$) that the agent plays its role in the electricity market by controlling and offering of its intercept (α_{jt}) [20]. The interactions of these strategic agents, independent system operator (ISO), non-strategic agents (demands), and renewable energy units are shown in Fig. 2.

In this paper, we consider elastic demands, which means that demands are not strategic, but they are assumed to react to the price change. This means they offer “Fixed Bid”. We consider renewable resources as feed-in-tariff. So, they do not offer bids in the electricity market. It means that they offer “Zero bid”.

As shown in Fig. 2, ISO receives bids from the agents and after clearing the market, the output power of the agents, and the locational marginal prices (LMPs) of each bus are calculated.

For this purpose, the following mathematical model is to be solved:

$$\text{Maximize}_{P_{G.jt}.\forall j; P_{D.it}.\forall i} \\ \sum_{i\in\Omega_D}\left(c_i P_{D.it} + \frac{1}{2} d_i P_{D.it}^2\right) - \sum_{j\in\Omega_G}\left(\alpha_{jt} P_{G.jt} + \frac{1}{2} b_j P_{G.jt}^2\right) \tag{1}$$

subject to:

$$\sum_{j\in\Omega_{G.z}} P_{G.jt} - \sum_{i\in\Omega_{D.z}} P_{D.it} = \sum_{m\in\Omega_B} \left(\frac{\delta_{zt}-\delta_{mt}}{x_{mz}}\right) \qquad \forall z \in \Omega_B \tag{2}$$

$$\left|\frac{\delta_{mt}-\delta_{zt}}{x_{mz}}\right| \leq P_{mz}^{\max} \qquad \forall m.z \in \Omega_B \tag{3}$$

$$P_{G.j}^{\min} \leq P_{G.jt} \leq P_{G.j}^{\max} \qquad \forall j \in \Omega_G \tag{4}$$

$$P_{D.i}^{\min} \leq P_{D.it} \leq P_{D.i}^{\max} \qquad \forall i \in \Omega_D \tag{5}$$

$$P_{G.jt}.P_{D.it} \geq 0 \qquad \forall j \in \Omega_G.\forall i \in \Omega_D \tag{6}$$

In this model, social welfare (1) is maximized subject to a set of constraints: balancing active power based on Kirchhoff current law for each bus is shown in (2). The active power across transmission lines, output power of generation units, and consumed energy by the loads are enforced to be within their limits as given in (3), (4), and (5), (6), respectively.

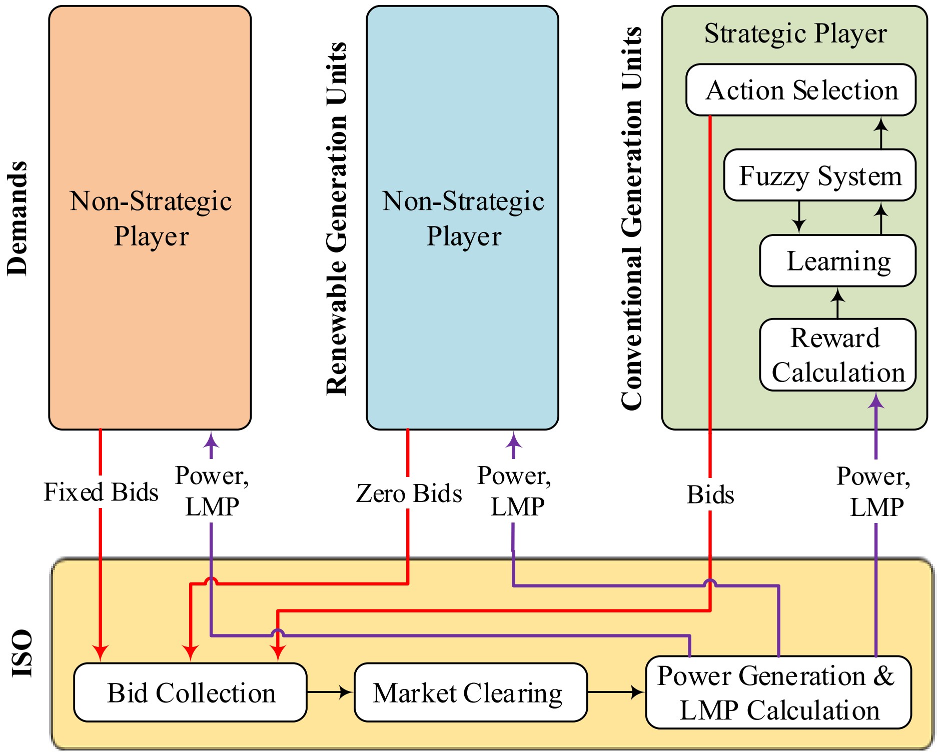

Fig. 2. Interaction between market agents.

According to Fig. 2, by feeding back the transmission buses' LMPs and the output power, each strategic player calculates its own profit by (7):

$$r_{jt} = LMP_{G.jt}P_{G.jt} - \left(u_j P_{G.jt} + \frac{1}{2} b_j P_{G.jt}^2\right) \tag{7}$$

In this paper, similar to that of [20], renewable power generation output is considered as the *state* and the intercept of bid function is defined as *action*. For example, if we have two renewable resources, then we have two states. Also, the calculated profit from (7) is considered as the agent *reward*.

In fuzzy *Q*-learning procedure, in each state, after receiving reward, Takagi-Sugeno fuzzy system becomes updated. For further explanation and mathematical formulation about updating procedure, the reader is referred to [20].

After updating the fuzzy system, the agent determines its next action (its preferred bid), and sends it to the ISO for the next hour market clearing. The action selection process is performed by ε-greedy approach using *Q* values of fuzzy system [20].

B. Market modelling indices

After accomplishing learning procedure described in subsection *A*, the market indices are evaluated. For this purpose, Ω_S as the set of all states (different values of RPP output power) is considered.

The average value of market indices over Ω_S is considered for evaluation procedure because of the possible renewable power intermittency. To this end, the considered RPP is examined in different candidate transmission buses and the average of indices over Ω_S is calculated for each of the buses. The candidate buses are selected based on geographical situation for the specific renewable generation which is to be expanded. The considered indices are presented in the follows. It is worth mentioning that this list is open to include any index which could be of interest for the market operators. Also, in the following equations, the asterisk is considered to differentiate the variables in this phase (testing) with the variables in the previous subsection (training).

1) Total load

RPP location affects the outcome of the electricity market. In this paper, we consider the average of total load as one of the indices for the assessment of the effects of RPP location:

$$TL = \sum_{i \in \Omega_D} P_{D.iT}^{*} \tag{8}$$

2) Standard deviation of LMP

This index reflects the LMP differences in all buses. The less standard deviation of LMP in a transmission system, the loads and generation units across the system experience the more equal price. Hence, the average of this index is considered in the assessment procedure proposed in this paper.

$$std_{LMP} = \sqrt{\frac{1}{N_B - 1} \sum_{n \in \Omega_B} \left(LMP^*_{nT} - \frac{1}{N_B} \sum_{n \in \Omega_B} LMP^*_{nT} \right)^2} \tag{9}$$

3) Average of Lerner index

Since by installing the new RPP, the conventional power generation units change their strategic behaviour, some of these market players might experience market power. In this regard, in this study, the average of market power index is considered as one of the indices.

One of the most frequently used market power indices is Lerner index [29] and its average is formulated as:

$$\mathrm{LI} = \frac{1}{N_G} \sum_{j \in \Omega_G} \frac{LMP^*_{G.jT} - (u_j + b_j P^*_{G.jT})}{LMP^*_{G.jT}} \tag{10}$$

4) Social welfare

The major objective of the electricity market clearing procedure is to maximize social welfare. RPP location might affect this index that is calculated as the difference between the overall benefit of the consumers and overall declared cost of the producers [30]:

$$SW = \sum_{i \in \Omega_D} \left(c_i P^*_{D.iT} + \frac{1}{2} d_i {P^*_{D.iT}}^2 \right) - \sum_{j \in \Omega_G} \left(\alpha^*_{jT} P^*_{G.jT} + \frac{1}{2} b_j {P^*_{G.jT}}^2 \right) \tag{11}$$

5) Congestion cost

Congestion is one of the barriers of free trading in electricity market. Several factors such as the low capacity of transmission network and load increase the effects of congestion. Congestion cost, which is an effective index for reflecting transmission congestion, is considered as one of the indices in this study and its average is calculated as [31]:

$$CC = \sum_{m \in \Omega_B} \sum_{n \in \Omega_B} P^*_{L.mnT} (LMP^*_{nT} - LMP^*_{mT}) \tag{12}$$

6) Sum of the generation units' declared cost

In electricity market, each generation unit offers its bid to the ISO for electricity market clearing depending on its real cost function. Generation unit's declared cost is calculated based on its offered bid. The following equation gives the sum of generation unit's declared cost:

$$TDC = \sum_{j \in \Omega_G} \alpha_{jT}^{*} P_{G.jT}^{*} + \frac{1}{2} b_j {P_{G.jT}^{*}}^{2} \tag{13}$$

Since the sum of declared cost of all generation units affects social welfare, it is considered as one of the indices in this study.

7) Nash index

In electricity market modelling approach, in each iteration, Nash index is defined equal to 1 if the play reaches to Nash equilibrium otherwise it yields 0, see [20].

8) Consumer payment

After market clearing, the LMP of each transmission buses is calculated and afterwards consumer payment is determined as one of the considered indices:

$$CP = \sum_{i \in \Omega_D} P_{D.iT}^{*} LMP_{D.iT}^{*} \tag{14}$$

C. Application of TOPSIS

After calculating the respective market indices, the candidate locations are evaluated and ranked by using TOPSIS. The calculation process of TOPSIS is shown in Fig. 3.

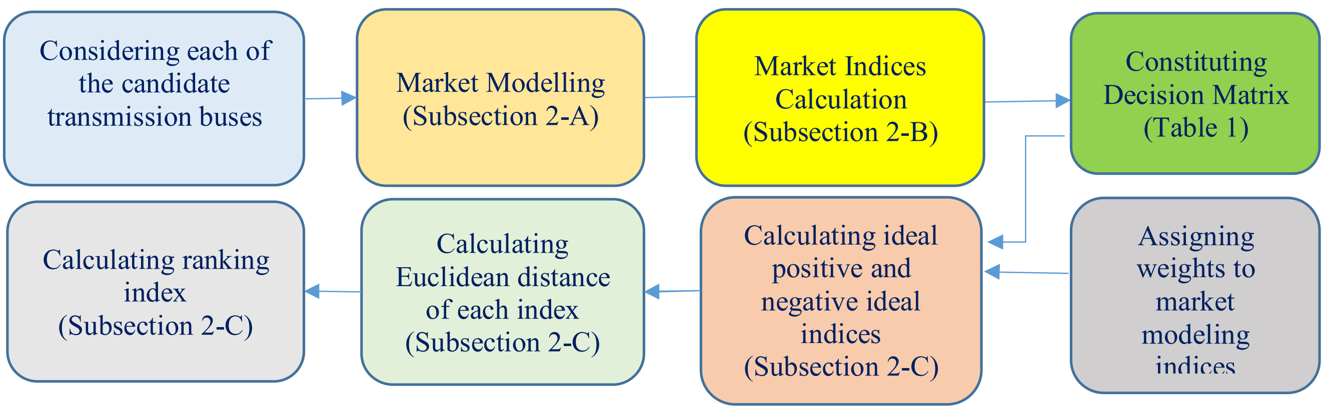

Fig. 3. *Evaluation procedure through TOPSIS.*

Each of the candidate transmission bus and its respective indices are shown in Table 1 as matrix H. For applying TOPSIS, each column should be normalized by dividing it by its respective infinite norm. By considering the essence of indices, it is found out that social welfare, total load, and Nash index are getting more preferable while they increase. However, the case for other 5 indices is vice versa. In order to homogenize all indices, we subtract the mentioned 3 indices by one. It is noted that the way to treat these homogenized indices in TOPSIS process is the same as that of [27]. The calculated matrix is Z.

The values of these market indices might vary in different transmission systems and electricity markets. Hence, we need to consider the weights for each index which have been provided by market operators.

Table 1 Typical Decision Matrix

	$\boldsymbol{I_1}$		$\boldsymbol{I_y}$		$\boldsymbol{I_N}$
O_1	h_{11}		h_{1y}		h_{1N}
O_x	h_{x1}		h_{xy}		h_{xN}
O_M	h_{M1}		h_{My}		h_{MN}

By multiplying each weight by the column of Z matrix, we have:

$$e_{xy} = z_{xy}.w_y \tag{15}$$

where w_y is weight for yth index and z_{xy} is the x,y entry of matrix Z. The ideal positive and negative ideal indices are calculated as:

$$e_y^{\max} = \max_x \; e_{xy} \tag{16}$$

$$e_y^{\min} = \min_x \; e_{xy} \tag{17}$$

Afterwards, the Euclidean distance of each index to the positive and negative ideal indices is calculated as:

$$O_x^+ = \sqrt{\sum_{y=1}^{N} \left(e_{xy} - e_y^{\max}\right)^2} \qquad x = 1.2. \dots M \tag{18}$$

$$O_x^- = \sqrt{\sum_{y=1}^{N} \left(e_{xy} - e_y^{\min}\right)^2} \quad x = 1.2. \dots M \tag{19}$$

where N is the number of indices and M is the number of candidate locations. Finally, ranking index (λ_x) is calculated as follows:

$$\varphi_x = \frac{O_x^-}{O_x^+ + O_x^-} \qquad x = 1.2. \cdots M \tag{20}$$

$$\lambda_x = \frac{\varphi_x}{\sum_{f=1}^{M} \varphi_f} \qquad x = 1.2. \cdots M \tag{21}$$

The related market indices of each candidate location with less λ_x are more preferable.

3. Test and Results

This section is organized as follows: General data and assumptions are brought in 3-A. To show the performance of the proposed approach, we devote 3-B to a wind power plant as the considered renewable resource.

A. General data and Assumptions

The proposed method is applied on IEEE 30-bus test system [32] and the results are analysed. As depicted in Fig. 4, six fossil-fueled generation units, whose cost functions and capacities are adopted from [18], are connected to this network.

Loads are assumed to be elastic and their related information is given in Table 2. It is assumed that a wind power plant is already installed in bus 10 which has a capacity of 20 MW.

The same investment cost and wind speed pattern is considered for investment of the new RPP in these buses. Because of possible network congestion, different RPP locations can cause different profits for the investor. The investor has very limited information from market, network and other participates. Because of the lack of enough information, the ISO helps the renewable power generation investors to find the best place for the new RPP installation.

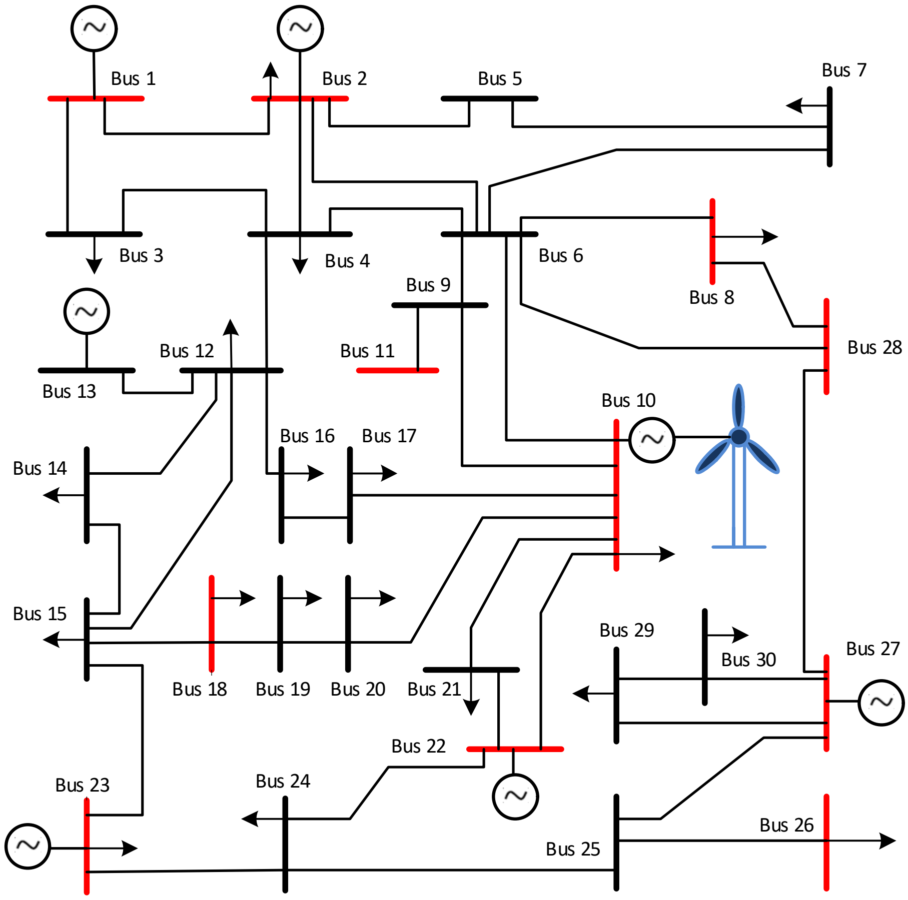

Fig. 4. *The modified IEEE 30-bus test system. The red buses* {1,2,8,10,11,18,22,23,26,27,28} *are considered as the candidate for the integration of new wind plant.*

Table 2 Demand Data

i	Bus	$P_{DMIN.i}$	$P_{DMAX.i}$	c_i	d_i	i	Bus	$P_{DMIN.i}$	$P_{DMAX.i}$	c_i	d_i
1	2	0	31.7	50	-0.1	**11**	17	0	19	53	-0.1
2	3	0	12.4	45	-0.1	**12**	18	0	13.2	45	-0.1
3	4	0	17.6	48	-0.1	**13**	19	0	19.5	44	-0.1
4	7	0	32.8	55	-0.1	**14**	20	0	12.2	60	-0.1
5	8	0	40	40	-0.1	**15**	21	0	27.5	45	-0.1
6	10	0	15.8	45	-0.1	**16**	23	0	13.2	35	-0.1
7	12	0	21.2	60	-0.1	**17**	24	0	18.7	42	-0.1
8	14	0	16.2	50	-0.1	**18**	26	0	18.5	57	-0.1
9	15	0	18.2	52	-0.1	**19**	29	0	12.4	44	-0.1
10	16	0	13.5	40	-0.1	**20**	30	0	20.6	50	-0.1

To this end, in this study, a new approach is proposed to help the renewable investors make the highest profit while improving the overall market indices at the same time.

The set of the provided bids for fossil-fueled generation units is shown in Table 3. It should here be noted that the RPPs are considered to adopt the feed-in-tariff as implied in different countries around the world. Also, the vector of weights $\left[\frac{1}{9},\frac{4}{27},\frac{4}{27},\frac{5}{27},\frac{4}{27},\frac{2}{27},\frac{1}{27},\frac{4}{27}\right]$ is assigned to the electricity market indices of subsection 2-B, respectively.

Table 3 Bid Set of fossil-fueled Generation Units

J	A_j	J	A_j
1	{20, 25, 30, 35, 40}	4	{10, 15, 20, 25, 30, 35, 40}
2	{20, 25, 30, 35, 40}	5	{30, 35, 40}
3	{30, 35, 40}	6	{35, 40}

B. ISO-Wind plant planner decision-making framework

It is also assumed that an investor decides to build a new wind power plant with a capacity of 30 MW which will be connected to transmission system. By considering the wind speed in different geographical areas in which the transmission system is expanded, 11 buses for this new RPP installation are considered as the candidates. These candidate buses are indicated in red font in Fig. 4. Also, Weibull distribution is used for characterization of wind speed. The Weibull PDF is $f_v(v) = (\frac{k}{c})(\frac{v}{c})^{k-1}e^{-(\frac{v}{c})^k}$ where k and c are shape and scale factors, respectively. The output power of a wind turbine is obtained as follows [33]:

$$P_{wr} = \begin{cases} 0 & v < v_{in} \quad v_{in} < v \\ av^3 + bP_r & v_{in} \le v \le v_r \\ P_r & v_r \le v \le v_{out} \end{cases} \tag{22}$$

where $a = \frac{P_r}{v_r^3 - v_{in}^3}$ and $b = \frac{v_{in}^3}{v_r^3 - v_{in}^3}$ [33]. Different geographical parameters are considered for the wind speed of the considered candidates that are shown in Table 4. It is worthy to highlight that we used fuzzy Q-learning modelling approach that we have proposed in our previous work [20]. Similar to that work, the state of each agent is considered as the output power of wind power generation and the action is its bid. The used fuzzy sets are depicted in Fig. 5.

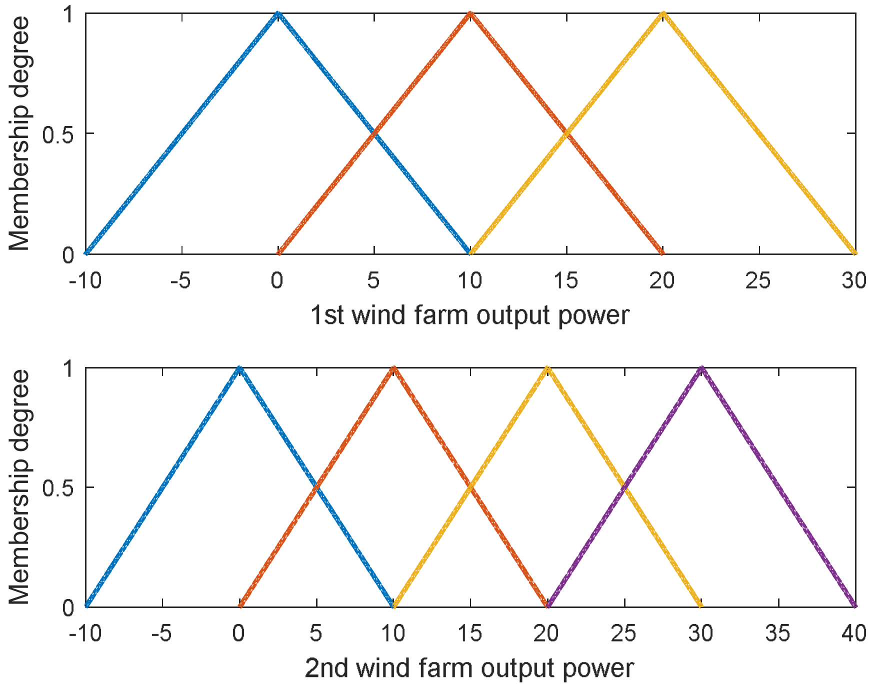

Fig. 5. *The wind plants' fuzzy sets*

For applying TOPSIS, we assumed that each market operator assigns a weight for each of the indices based on its preference. Similar to any machine learning approaches, fuzzy Q-learning has two phases: training and testing. In the training phase, the aim is to provide the agents with this possibility to experience all states through a sufficient number of iterations. If we use Weibull distribution and Eq. (22), a very large number of iterations is required to provide the agents with this possibility to experience the states with low probability. To tackle this problem, we use uniform distribution to experience all the points of the ranges of 0-20 and 0-30 MW in a lower number of iterations. However, in the testing phase, we use Weibull distribution and Eq. (22) for characterization of the output power of wind turbines in different buses. By deploying the proposed method of Section III, fuzzy Q-learning approach has been performed 50000 times for each of the candidate locations.

It is noted that ε-greedy approach (ε is equal to 0.1) is considered as the action selection technique in the simulation. The learning rate of fuzzy Q-learning approach is 0.2. Based on the definition of *state* in our reinforcement learning – based problem which is renewable power generation output, in this paper, we have two states, the first one is related to the output of wind farm of bus 10 and the second is related to the wind plant which is going to be located in the candidate bus. For the first and second states, 3 and 4 triangular fuzzy sets are considered, which cover 0-20 and 0-30 MW in a uniform spacing, respectively.

Table 4 Wind distribution data in different bus locations

bus	c	k	v_{in}	v_{out}	v_r
1	15	3	3	30	12
2	16	2	3	30	12
8	17	3	3	30	12
10	15	1	3	30	12
11	12	2	3	30	12
18	11	1	3	30	12
22	16	3	3	30	12
23	17	1	3	30	12
26	18	3	3	30	12
27	15	2	3	30	12
28	13	1	3	30	12

After finishing the market modelling procedure, the market indices are derived for each wind plant location. Then, different locations are sorted by applying TOPSIS. The iteration number for learning through fuzzy Q-learning approach is set as 50000. This number of iterations is sufficient for all q values to be evolved and therefore all generation units reach to their evolved bidding strategy.

In Fig. 6, the q values related to rule R22 corresponding to generation unit 2 when the new wind plant is located in bus 1 is depicted. More information about the used Takagi-Sugeno fuzzy rules is referred to subsection 3.2 of [20]. As shown in Fig. 6, the q values are settled after about 20000 iterations, which is less than 50000.

The market indices and the average profit for the wind plant are given in Table 5. As shown in this table, the maximum of average wind plant's profit is 1121 [$/h] which is realized in bus 8. In Table 5, the corresponding row is shown in red. Also, by considering the vector of weights $\left[\frac{1}{9},\frac{4}{27},\frac{4}{27},\frac{5}{27},\frac{4}{27},\frac{2}{27},\frac{1}{27},\frac{4}{27}\right]$for all of the indices, bus 26 is selected as the best location for wind plant investment from the prospective of electricity market indices by applying TOPSIS. The corresponding row is shown in green. Based on the proposed method, the investor is motivated to locate its wind plant in bus 26 by providing him/her with 1121-1038, i.e., 83 $/h as the investment incentive. This procedure is considered as a win-win decision from the prospective of renewable energy investment and electricity market behavior as shown in Table 5. By installing the wind plant in bus 26, the market indices are improved even in comparison with the case of before installing wind plant.

For demonstrating the advantages of selecting bus 26 as wind plant installation bus, three fairness reflective indices of Table 5 including std_LMP, congestion cost and social welfare are normalized and compared.

The comparison result shows that the values of std_LMP, congestion cost, and social welfare are respectively 61% less, 60% less and 3% higher than those of the average related values in all candidate buses. The related normalized values are shown in Fig. 7. From this figure, it is also observed that the studied electricity market has been improved by installing wind plant in bus 26 in comparison with the case study before the investment.

As another result of implementing TOPSIS, the ranking of transmission buses from the prospective of electricity market indices is calculated and depicted in an ascending order in Fig. 8. As mentioned before, it is also understood from this figure that installing the wind plant in bus 26 has the most positive impact and, in contrast, investment in bus 22 has the least positive impact on the electricity market indices.

Fig. 9 shows the LMP of the new wind plant when it is installed in bus 26 and bus 28. From this figure it can be inferred that installing wind plant in different locations can cause very different LMP profiles for new wind plant, and therefore it can change its average profit.

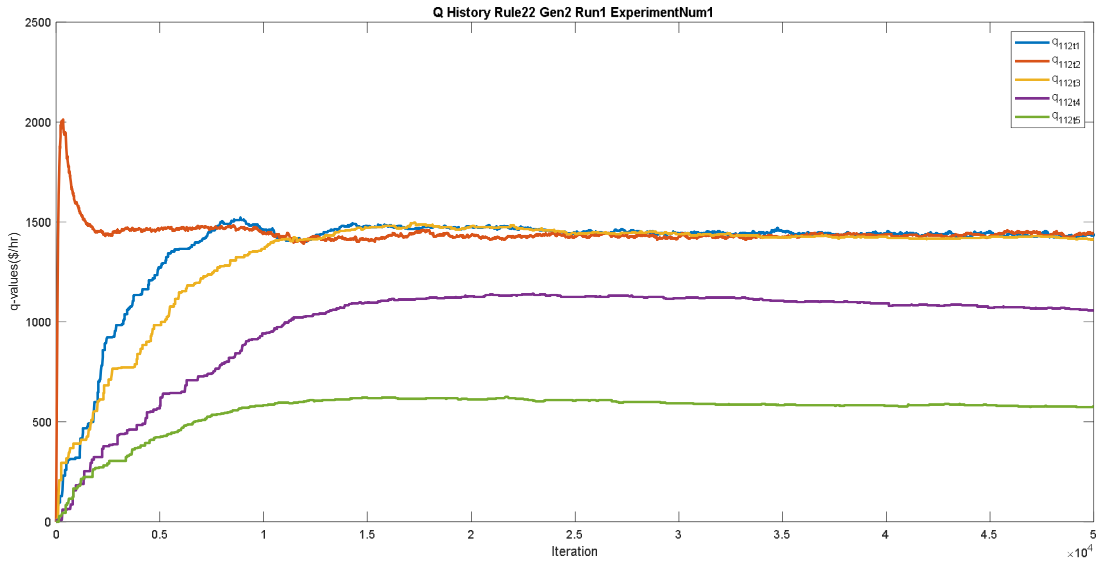

Fig. 6. *Development of fuzzy system variables corresponding to generation unit 2 when the new wind plant is located in bus 1.*

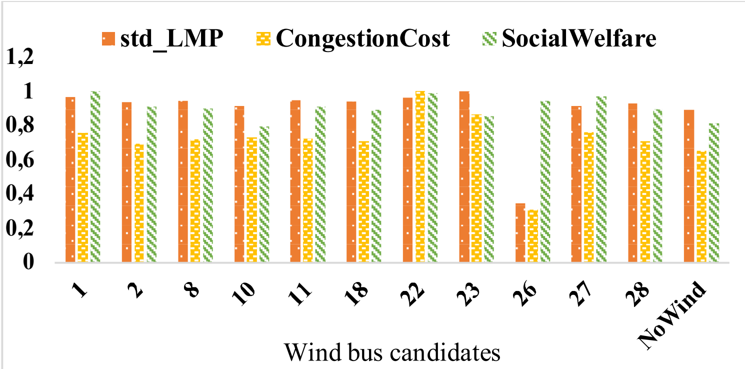

Fig. 7. Normalized market indices for wind plant candidate location.

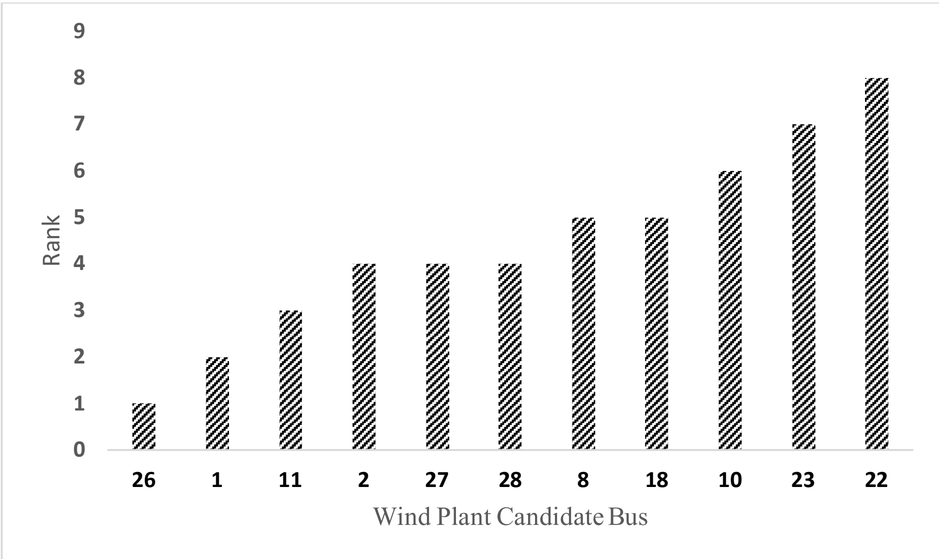

Fig. 8. Ranking of difference wind plant locations based of market indices.

Table 5 Average of market indices and wind plant's average profit

Candidate Bus	$\overline{TL}$ [MW]	$\overline{std}_{LMP}$ [\$/MWh]	$\overline{LI}$	$\overline{SW}$ [\$/h]	$\overline{CC}$ [\$/h]	$\overline{TDC}$ [\$/h]	$\overline{NI}$	$\overline{CP}$ [\$/h]	New RPP Profit [\$/h]
1	311	2.61	0.14	6677	350	8612	0.78	13190	921
2	306	2.53	0.15	6100	322	9017	0.64	13075	817
8	307	2.55	0.15	6015	333	9136	0.55	13086	1121
10	286	2.47	0.18	5316	339	8922	0.45	12498	633
11	311	2.56	0.13	6081	336	9204	0.37	13226	668
18	304	2.54	0.15	5959	329	9067	0.43	13013	450
22	304	2.60	0.17	6600	464	8413	0.31	13011	956
23	305	2.70	0.14	5711	401	9323	0.52	13179	394
26	307	0.93	0.17	6314	144	8872	0.33	13078	1038
27	301	2.47	0.16	6478	354	8400	0.93	13019	841
28	305	2.51	0.15	5984	329	9083	0.71	13103	551
No Wind	297	2.40	0.16	5447	302	9281	0.61	12928	0

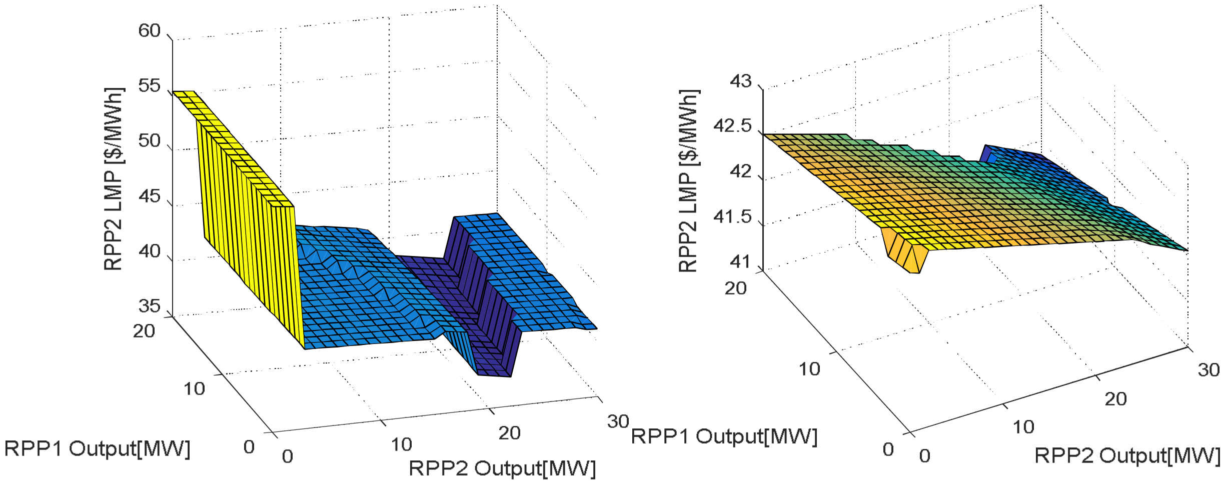

Fig. 9. *RPP2's profit for various RPP's output when RPP 2 is located in bus 26 (left) and bus 28 (right).*

The simulation results show that the proposed mechanism is able to successfully support a considered renewable investment plan by firstly determining the maximum achievable profit and secondly giving an incentive to the investor to motivate him/her to locate the intended renewable generation plan in a bus in which electricity market indices are improved substantially. For example, $\overline{std_{LMP}}$, $\overline{CC}$, and $\overline{SW}$ are improved 61.2%, 52.3%, 15.9% respectively after installing the wind plant in the achieved optimal location. It is worthy to mention that some of the market indices such as the standard deviation of LMP are able to guarantee fairness in electricity market.

4. Conclusion

Renewable energy promotion is an inevitable task of the energy sector for preventing the ever-increasing climate change. In this regard, a new interactive multi-criteria decision-making framework between ISO and a renewable power plant planner is proposed in this paper for simultaneously supporting the intended renewable power generation plan and improving electricity market indices. The support mechanism has been developed by providing an incentive mechanism. The incentive mechanism provides the maximum achievable profits for the investor while gaining the most possible improvement in electricity market behavioral indices. This point is considered as a major research gap that is attempted to be filled in this paper in a way to simultaneously help the investor achieve its maximum profit and the market operator benefit from improving the electricity market indices. To this end, a combination of multi-agent fuzzy Q-learning modelling approach with TOPSIS is deployed to determine the best location from the prospective of renewable investor's profit and the best preferable location from the viewpoint of the market operator. One of the advantages of this method is to simulate and consider the strategic behavior of the other generation units after connecting the renewable power generation plan to each of the transmission buses. Simulations have been performed on the IEEE 30-bus test system and the results have been analyzed. The simulation results show that by applying the proposed method the market indices have been improved. For example, $\overline{std_{LMP}}$, $\overline{CC}$, and $\overline{SW}$ are improved 61.2%, 52.3%, 15.9% respectively after installing the wind plant in the achieved optimal location. As a future outlook, the proposed approach can be developed for other types of renewable resources, such as solar power plants. Also, besides market indices, reliability criteria can be considered for proposing a reliability-based support for promotion of renewable energy.

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