Adaptive neuro-fuzzy optimization of wind farm project net profit

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A wind power plant which consists of a group of wind turbines at a specific location is also known as wind farm. To maximize the wind farm net profit, the number of turbines installed in the wind farm should be different in depend on wind farm project investment parameters. In this paper, in order to achieve the maximal net profit of a wind farm, an intelligent optimization scheme based on the adaptive neuro-fuzzy inference system (ANFIS) is applied. As the net profit measures, net present value (NPV) and interest rate of return (IRR) are used. The NPV and IRR are two of the most important criteria for project investment estimating. The general approach in determining the accept/reject/stay in different decision for a project via NPV and IRR is to treat the cash flows as known with certainty. However, even small deviations from the predetermined values may easily invalidate the decision. In the proposed model the ANFIS estimator adjusts the number of turbines installed in the wind farm, for operating at the highest net profit point. The performance of proposed optimizer is confirmed by simulation results. Some outstanding properties of this new estimator are online implementation capability, structural simplicity and its robustness against any changes in wind farm parameters. Based on the simulation results, the effectiveness of the proposed optimization strategy is verified.

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1. Introduction

The world’s fastest growing renewable energy source is the wind energy. Wind turbines are machines which convert the wind energy to the electricity [1,2]. A wind farm contains a number of horizontal wind turbines [3,4]. These wind turbines are positioned and aligned in clusters facing the wind direction. Optimal wind turbine placement on a selected wind farm site is of major importance, since it can lead to a remarkable increase in the produced power and therefore the overall net profit of the wind farm [5–7].

Besides the optimal wind turbine placement, the number of wind turbines installed in the wind farm can also be of major importance to achieve the maximal produced power and net profit of the wind farm. In this article the main focus will be on number of turbines modifying by taking economic aspects into account [8]. Conceptual design of a new wind farm involves the evaluation of alternative farm configurations to determine physical and economic feasibilities [9]. In testing alternatives, designers require both an absolute economic measure and a normalized economic measure in order to make a definitive evaluation [10,11]. In recent years NPV (Net Present Value) [12–16] has often been chosen as the absolute metric and IRR (Internal Rate of Return) [17–19] as the normalized one.

The NPV and IRR are two of the most important criteria for choosing among investment projects [20,21]. In many circumstances investment projects are ranked in the same order by both criteria. In [22] was consider the NPV and IRR as indexes to evaluate the investment risk of wind power project. Paper [23] presented an alternative approach to conceptual design where a compound objective function based on the NPV and IRR aggregate performance metrics. In some situations, however, the two criteria provide different rankings [24]. In [25,26] a sensitivity analysis of the IRR to some economic factors has been carried out.

In an uncertain economic environment, it is usually difficult to predict accurately the investment outlays and annual net cash flows of a project [27]. In addition, available investment capital sometimes cannot be accurately given either [28]. In [29] was addressed the maximization of a project’s expected NPV when the activity durations and cash flows are described by a discrete set of alternative scenarios with associated occurrence probabilities. Article [30] presented the concept of NPV curve to estimate the
best investment time for the investor, where the curve is constructed by calculating the NPVs resulting from the investment in successive years.

Optimal performance (maximal net profit) of the wind farm can be obtained if the number of turbines installed in the wind farm is optimal. The aim of the investigation is to change the number of turbines in the wind farm at different interest rates per year and unit sale price of electricity so that the farm may be kept running at maximum profit level or to maximize NPV.

To improve the operations of the wind farm, application of fuzzy logic (FL) [31–36] or artificial neural network (ANN) has attracted much attention in recent years [37–43]. As a soft computing [44], non-linear function, ANNs can be used for identifying the extremely non-linear system parameters with high accuracy. Neural networks can learn from data. However, understanding the knowledge learned by neural networks has been difficult. In contrast, fuzzy rule based models are easy to understand because they use linguistic terms and the structure of IF-THEN rules. Unlike neural networks, however, fuzzy logic by itself cannot learn. Since neural networks can learn, it is natural to merge these two techniques. This merged technique of the learning power of the ANNs with the knowledge representation of FL has created a new hybrid technique, called neuro-fuzzy networks or adaptive neuro-fuzzy inference system (ANFIS) [45]. ANFIS, as a hybrid intelligent system that enhances the ability to automatically learn and adapt, was used by researchers for modeling [46–49], predictions [50–54] and control [55–59] in various engineering systems. ANFIS can be used with systems handling more complex parameters than neural networks or fuzzy logic. Another advantage of ANFIS is its speed of operation, which is much faster than in other control strategies like neural networks or fuzzy logic. A limit to the maximum extractable kinetic energy from the wind by a wind turbine was determined to be 59.3% by Betz [69], and is appropriately termed the Betz limit. Betz formulated the limit using simple one dimensional Bernoulli equation to model incompressible wind flow across the rotor. The assumptions used in the derivation were a constant, uniformly distributed velocity and pressure profile across the turbine's seeping area. Due to this model is one dimensional, tip losses due to rotational effects and viscous dissipation are neglected. The Betz limit cannot be achieved with wind turbines due to aerodynamic losses by interactions between turbines, viscous dissipation, and efficiency losses though mechanical and electrical power converting devices.

The Jensen’s wake has a radius, at the turbine which is equal to the turbine radius $R_t[m]$ while, $R_1[m]$ is the radius of the wake in the model. $R_t[m]$ is considered as radius of the downstream wake; the relationship between $R_1$ and $X[m]$ is that downstream distance when the wake spreads downstream the radius $R_1$; that increases linearly proportional, $X$; axial induction factor is denoted by $a$; $z$ is the entertainment constant. The wake expands linearly with downstream distance, as stated in Jensen’s model as shown in Fig. 1.

Following equation [68] is used to determine the wind speed after wind turbine rotor as it shown in Fig. 1:

$$u = u_0 \ast \left(1 - \frac{2a}{1 + z \left(\frac{x}{(6 \sqrt{a})}\right)^2}\right)^2$$ (1)

In a wind farm, some turbine might or might not be affected by the wake created by another turbine positioned in front of it. Moreover, the effect might be partial or complete. Eq. (1) represents complete wake effect of a wind turbine in front of another. Another interesting state of the wake effect is when a portion of a turbine is affected simultaneously by the wake of two wind turbines as it shown in Fig. 2.

Following equation [68] is used to determine the wind speed for multiple partial interferences of the wake effects after the two wind turbine rotors as it shown in Fig. 2:

$$u_{i+1} = u_i \ast \left(1 - \frac{2a}{1 + z \left(\frac{x}{(6 \sqrt{a})}\right)^2}\right)^2 + \frac{2a}{1 + z \left(\frac{x}{(6 \sqrt{a})}\right)^2}$$ (2)

2. Wind farm power production model

Since a wind turbine generates electricity from the energy in the wind, the wind leaving the turbine has less energy content than the wind arriving in front of the turbine. Therefore a wind turbine in a wind farm will always cast a wind shadow in the downwind direction. This is described as the wake behind the turbine, which is quite turbulent and has an average down wind speed slower than the wind arriving in front of the turbine.

For the present study analytical wake model named as Jensen’s wake model [68] is chosen. The wake model is based on the Betz theory [69]. Betz theory is useful in determining the wake wind speed after the rotor. The principle of wind turbines is to extract kinetic energy from the wind and convert it into electricity. A limit to the maximum extractable kinetic energy from the wind by a wind turbine was determined to be 59.3% by Betz [69], and is appropriately termed the Betz limit. Betz formulated the limit using simple one dimensional Bernoulli equation to model incompressible wind flow across the rotor. The assumptions used in the derivation were a constant, uniformly distributed velocity and pressure profile across the turbine's seeping area. Due to this model is one dimensional, tip losses due to rotational effects and viscous dissipation are neglected. The Betz limit cannot be achieved with wind turbines due to aerodynamic losses by interactions between turbines, viscous dissipation, and efficiency losses though mechanical and electrical power converting devices.

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\[ P_T = \sum_{i=1}^{N_t} \frac{1.2 \times u_i^3}{2} \]

where \( N_t \) represents the turbines number in wind farm.

3. Definition of NPV and IRR

Capital budgeting is finance terminology for the process of deciding whether or not to undertake an investment project. There are two standard concepts used in capital budgeting: net present value (NPV) and interest rate of return (IRR) \[16,17\].

The purpose of the NPV is to represent the value, or worth, of a stream of payments in a single number, recognizing the fact that the same nominal payment, made at different times, will have different worth. The NPV of a stream of payments is defined to be the sum of the discounted values of the individual terms in the stream, where each term is discounted to a common reference date. The IRR of such a payment stream is defined to be any discount rate for which the NPV of the payment stream is zero \[20,21\].

NPV is the net present value which is the sum of all the future cash flows to determine the present value. Cash flows include both inflows and outflows that are discounted at a rate. It is calculated as \[20\]:

\[
NPV = \text{Cash Inflows} - \text{Cash Outflows}
\]

The NPV of a project is the sum of the present value of all its cash flows, both inflows and outflows, discounted at a rate consistent with the project’s risk.

The NPV determines whether or not a specific project is worthwhile \[20\]. Suppose a project has cash flows \( CF_0, CF_1, CF_2, \ldots, CF_n \). Suppose that the appropriate discount rate for this project is \( r \). Then the NPV \[21\] of the project is

\[
NPV = -CF_0 + \frac{CF_1}{1 + r} + \frac{CF_2}{(1 + r)^2} + \ldots + \frac{CF_n}{(1 + r)^n}
\]

\[
= -CF_0 + \sum_{t=1}^{n} \frac{CF_t}{(1 + r)^t} \tag{11}
\]

\( CF_0 \) - initial cash flow required to implement the project. This is usually a negative number.

A project is worthwhile by the NPV rule if its \( NPV > 0 \). In this expression \( CF_t \) represents net cash flow in the year \( t \), \( r \) is the discount rate and \( n \) represents the life of the project.

The NPV determines which project will be accepted between two mutually exclusive projects \[20\]. Suppose project A has cash flows \( CF_0^A, CF_1^A, CF_2^A, \ldots, CF_n^A \), and project B has cash flows \( CF_0^B, CF_1^B, CF_2^B, \ldots, CF_n^B \) \[21\]. Project A is preferred to project B if

\[
NPV(A) = -CF_0^A + \sum_{t=1}^{n} \frac{CF_t^A}{1 + r} > -CF_0^B + \sum_{t=1}^{n} \frac{CF_t^B}{1 + r} \tag{12}
\]

The logic of both NPV rules presented above is that the present value of a project’s cash flows \[16\]

\[
PV = \sum_{t=1}^{n} \frac{CF_t}{(1 + r)^t} \tag{13}
\]

represents the economic value today of the project. Thus, if the discount rate \( r \) is correctly chosen for the project, the \( PV \) is what we ought to be able to sell the project for in the market. The net present value is the wealth increment produced by the project, so that \( NPV > 0 \) means that a project adds to our wealth \[16\]:

\[
NPV = -CF_0 + \sum_{t=1}^{n} \frac{CF_t}{(1 + r)^t} \tag{14}
\]
An alternative to using the NPV criterion for capital budgeting is to use the internal rate of return (IRR). IRR is defined as the discount rate for which the NPV equals zero. It is the compound rate of return that you get from a series of cash flows. NPV describes the value of investment in amount but IRR shows the amount in percentage. IRR is used to determine that what rate of return an investor is taking on a project. IRR provides the answer in percentage. It is actually based on the present value concept, the amount of money which you receive today has more worth than you receive tomorrow. IRR is actually the capital budgeting technique which actually equates the NPV answer to the initial investment or cost. Here are the two decision rules for using the IRR in capital budgeting [20, 21].

The IRR determines whether or not a specific investment is worthwhile [21]. Suppose we are considering a project that has cash flows $CF_0, CF_1, CF_2, \ldots, CF_n$. IRR is an interest rate such that [12]

$$-CF_0 + \frac{CF_1}{(1 + IRR)^1} + \frac{CF_2}{(1 + IRR)^2} + \ldots + \frac{CF_n}{(1 + IRR)^n} = 0 \quad (15)$$

If the appropriate discount rate for a project is $r$, you should accept the project if its IRR > $r$ and reject it if its IRR < $r$. The logic behind the IRR rule is that the IRR is the compound return you get from the project. Since $r$ is the project’s required rate of return, it follows that if the IRR > $r$, you get more than you require.

IRR is used to evaluate that which one investment is providing comparatively better rate of return. Some investors prefer to use IRR as to take decision on the basis of required rate of return calculated in percentage. Financial managers prefer to use IRR. The preference for IRR is due to the general disposition of businesspeople towards rate of return rather actual money return. They tend to find NPV less intuitive because it does not measure the amount relative to the amount invested. But some investors prefer to use the NPV because it evaluates the investment project in amount. In amount or money value it is easily to understand that what a project is providing in return but in IRR it is difficult to evaluate. It is because the IRR gives answer in percentage which in many cases become difficult for investors to evaluate return. NPV project evaluation is superior to that of IRR. NPV discounts all the cash flows to present to see whether the investment project will cause benefit or loss to the investor.

The IRR determines which project will be accepted between two competing projects [21]. Suppose you are trying to decide between two mutually exclusive projects A and B. Suppose project A has cash flows $CF_0^A, CF_1^A, CF_2^A, \ldots, CF_n^A$, and that project B has cash flows $CF_0^B, CF_1^B, CF_2^B, \ldots, CF_n^B$ [20]. Project A is preferred to project B if

$$\text{IRR}(A) > \text{IRR}(B) \quad (16)$$

Since the IRR gives a project’s compound rate of return, if we choose between two projects using the IRR rule, we prefer the higher compound rate of return.

4. NPV for wind farm project investment

Net present value, NPV, of the profit to be derived from the wind farm is

$$\text{NPV} = -CF_0 + \sum_{i=1}^{n} \frac{T \times P_i \times (\text{CPPU}, \text{C}, \text{E}, N_i) + \text{CU} - M}{(1 + r)^t}$$

$$= -CF_0 + \sum_{i=1}^{n} \frac{CF_i}{(1 + r)^t} \quad (17)$$

where $CF_0$ represents total investment in the wind farm (cost of turbines, installations and land cost), $CF_i$ is the net revenue from selling electricity from the wind farm, $r$ is the appropriate financial interest rate, $T$ is total operating time per period, $n$ is the number of years for project investment, $P_i$ is the total extracted power from all wind turbines in the wind farm and it depends on total cost $C$, cost per power unit $\text{CPPU}$, efficiency $E$ and the number of turbines $N_i$. $\text{CU}$ is the unit sale price of electricity and $M$ is the cost of operation and maintenance of the wind farm per period.

Interest rate of return, IRR, can be derive when the $\text{NPV} = 0$ or

$$0 = -CF_0 + \sum_{i=1}^{n} \frac{T \times P_i \times (\text{CPPU}, \text{C}, \text{E}, N_i) + \text{CU} - M}{(1 + IRR)^t}$$

$$= -CF_0 + \sum_{i=1}^{n} \frac{CF_i}{(1 + IRR)^t} \quad (18)$$

In this study the used values for different variables and parameters are as under:

$$X = 200 \text{ m}$$

$$R_i = 20 \text{ m}$$

$$u_0 = 12 \text{ m/s}$$

$$a = 0.326795$$

$$\alpha = 0.09437$$

$$N_i = 1 – 100 \text{ turbines}$$

$$r = 1 – 10\% \text{ per year}$$

$$T = 7884 \text{ h/year}$$

$$\text{CU} = 0.6 – 1.5 \text{ $/kW h}$$

$$CF_0 = N_i \times (CT + CL + CL \times (N_i))$$

$$CT = 450,000$ – cost per turbine

$$CL = 100,000$ – cost per turbine installation

$$CL = 100$ – cost of land per turbine

$$M = 0.015 \times CT \times N_i$$

Fig. 3 shows four cases where NPV always increase with larger number of wind turbines in the wind farm. The figure shows that with the smaller interest per year $r$ the net profit will be higher. Also decreasing of the unit sale price for electricity will decrease the overall net present value of the wind farm. The all four cases depicted in the figure shows that the maximal NPV will occur for the highest number of turbines installed in wind farm – the red circles.

It is useful to analyze also interest rate of return (IRR) for the wind farm project investment. Fig. 4 shows the IRRs for the four cases mentioned in the Fig. 3. It can be seen that the maximal IRR occurs for the smallest number of turbines installed in the wind farm. The IRRs decreases for increasing number of turbines in the wind farm. Fig. 4 shows one interesting case for the same unit sale price of electricity $\text{CU} = 0.8 \text{ $/kW h}$ and the cost of capital $r = 1\%$ and $r = 3\%$. It can be seen that the IRRs are the same for the cases (solid line). The project is accepting while the IRR is greater than the cost of capital $r$. The all four cases in Fig. 4 shows the accepting projects since the IRRs are greater than the predetermined cost of capitals $r$.

However, there are the some cases where the net profit of the wind farm project investment is not the highest for the maximal number of turbines installed in the wind farm. Fig. 5 depicts 4 cases where NPV decreases when number of turbines installed in wind farm is higher than optimal number of turbines. It means that the optimal number of the turbines for the maximal NPV will be between 1 and 100. There are some cases when the NPV is negative or it means that it will be detriment for the project investment. The red circles depict the optimal points (maximal NPV) for the cases of the wind farm project investments.
Fig. 6 shows the IRRs for the four cases mentioned in the Fig. 5. It can be also seen that the maximal IRR occurs for the smallest number of turbines installed in the wind farm. The IRRs decreases for increasing number of turbines. The project is accepting while the IRR is greater than the cost of capital $r$. The IRR for project with cost of capital $r = 8$ and for the unit sale price of electricity $CU = 1.1$ is smaller than the cost of capital after specified number of wind turbines. It means the project is unaccepting for the larger number of turbines.

5. Adaptive neuro-fuzzy inference system

Fuzzy Inference System (FIS) is the main core of ANFIS [45]. FIS is based on expertise expressed in terms of ‘IF–THEN’ rules and can thus be employed to predict the behavior of many uncertain systems. FIS advantage is that it does not require knowledge of the underlying physical process as a pre-condition for its application. Thus ANFIS integrates the fuzzy inference system with a back-propagation learning algorithm of neural network. The basic structure of a FIS consists of three conceptual components: a rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions (MFs) used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and the given facts to derive a reasonable output or conclusion. These intelligent systems combine knowledge, technique and methodologies from various sources. They possess human-like expertise within a specific domain – adapt themselves and learn to do better in changing environments. In ANFIS, neural networks recognize patterns, and help adaptation to environments. ANFIS is tuned with a back propagation algorithm based on the collection of input-output data [45].

ANFIS model will be established in this study to estimate the optimal number of wind turbines in wind farm for the project investment in relation to the two parameters, cost of capital or interest rate per year and unit sale price of electricity. Training and checking data for the ANFIS networks is extracted from the Eq. (15). With a proper training scheme and fine filtered data-sets, ANFIS is capable to estimate optimal number of turbines quite accurately since it learns from training data. This measurement-free architecture also makes it immediately available for operation once they are trained.

In this work, the first-order Sugeno model with two inputs and fuzzy IF–THEN rules of Takagi and Sugeno’s type [45] is used: if $x$ is $A$ and $y$ is $C$ then $f_1 = p_1 x + q_1 y + r_1$ (19)
The first layer consists of input variables membership functions (MFs) A, B, C and D. This layer just supplies the input values to the next layer. In the first layer every node is an adaptive node with a node function

\[ O_i = \mu(x_i) \]

where \( \mu(x_i) \) are MFs.

In this study, bell-shaped MFs (17) with maximum equal to 1 and minimum equal to 0 is chosen

\[ f(x; a, b, c) = \frac{1}{1 + (\frac{x-c}{a})^2} \]

where the bell-shaped function depends on three parameters \( a, b \) and \( c \). The parameter \( b \) is usually positive. The parameter \( c \) located the center of the curve as it is shown in Fig. 8.

The second layer (membership layer) checks for the weights of each MFs. It receives the input values from the 1st layer and acts as MFs to represent the fuzzy sets of the respective input variables. Every node in the second layer is non-adaptive and this layer multiplies the incoming signals and sends the product out like

\[ w_i = \mu(x_i) \mu(x_{i+1}) \]

Each node output represents the firing strength of a rule or weight.

The third layer is called the rule layer. Each node (each neuron) in this layer performs the pre-condition matching of the fuzzy rules, i.e. they compute the activation level of each rule, the number of layers being equal to the number of fuzzy rules. Each node of these layers calculates the weights which are normalized. The third layer is also non-adaptive and every node calculates the ratio of the rule's firing strength to the sum of all rules' firing strengths like

\[ w_i^r = \frac{w_i}{\sum w_i} \]

\[ i = 1, 2. \]

The outputs of this layer are called normalized firing strengths or normalized weights.

The fourth layer is called the defuzzification layer and it provides the output values resulting from the inference of rules. Every node in the fourth layer is an adaptive node with node function

\[ O_i^f = w_i f_i = w_i (p_i x + q_i y + r_i) \]

where \( \{p_i, q_i, r_i\} \) is the parameter set and in this layer is referred to as consequent parameters.

The fifth layer is called the output layer which sums up all the inputs coming from the fourth layer and transforms the fuzzy classification results into a crisp (binary). The output represents estimated modulation transfer function of the optical system. The single node in the fifth layer is not adaptive and this node computes the overall output as the summation of all incoming signals

\[ O_i^o = \sum_i w_i^r f_i = \frac{\sum w_i^r f_i}{\sum w_i^r} \]

The hybrid learning algorithms were applied to identify the parameters in the ANFIS architectures. In the forward pass of the hybrid learning algorithm, functional signals go forward until Layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backwards and the premise parameters are updated by the gradient descent.

### 6. Results

At the beginning the ANFIS network was trained. The training data is shown in Fig. 9 where x-axis represents experimental
training data samples (250) and the output or y-axis in the Fig. 9 depicts the optimal number of wind turbines installed in wind farm. These training data are acquired by above presented mathematical procedure. The other 250 experimental data samples are used for testing of the proposed model.

Fig. 10 shows training procedure for the ANFIS network. It can be seen that the minimal RMS error was achieved after 35 epochs and it was 2.1446.

Three bell-shaped membership functions were used for each input during training procedure. It is not appropriate to further increase the number of the membership functions since there are too many parameters to estimate. After training process the ANFIS network was tested. Fig. 11 shows the result of the testing of the ANFIS network. It can be depicted good ANFIS prediction (red stars) of the presented data.

The final decision surface after training procedure of the ANFIS network is shown in Fig. 12. This surface represents optimal values for the number of wind turbines installed in wind farm. The proposed optimizer should follow this surface in order to achieve optimal values of the number of wind turbines. It can be noted some negative parts of the surface which is not logical since the number of turbines cannot be negative. The negative parts indicate inputs are not logical for that outputs in real applications.

Fig. 13 shows the ANFIS prediction errors of the optimal number of wind turbines for the experimental dataset. The maximum deviation was 5 and the minimum deviation was −4.7 from the experimental data.

The optimal number of the wind turbines ANFIS estimation is implemented in MATLAB Simulink block diagrams as it shown in Fig. 14. It shows block diagram for estimation of the optimal number of the wind turbines installed in wind farm to achieve maximal net profit of the wind farm project. In the Simulink diagram can be seen that for interest rate per year 5% and unit sale price of electricity 0.7 $/kWh, the optimal number of the wind turbines is 23. The It can be noted the rounding function block in the Simulink diagram since the number of turbines should be whole number. This approach is very useful for fast estimation of the optimal number of wind turbines according to the main project investment parameters of the wind farm.
In this study, Fig. 15 shows the part of the proposed layout of the wind turbines placement, which shows that first 2 wind turbines of first row and 2 wind turbines in second row of placed wind turbines are directly facing the maximum wind speed without small reduction. Fig. 15 shows only part of the wind farm since the optimal number of the wind turbines are 23. The main point is to show how two wind turbines affect one wind turbine by wake interactions. Multiple partial interferences of the wake effects occurred, as it shown in Fig. 2. Yellow arrows (X) represent distances between turbines or in this case downstream wake distance. In this investigation we do not use parameter which describes number of the rows in wind farm only distance between the turbines.

7. Conclusion

The deregulation of the energy sector resulted in a new economic environment, due to the daily operations of the electric markets, and this new environment needs to be considered with the economics of investment in new facilities. The long-term horizon with the sequence of appropriate decisions adds to the complexity of the problem. A future investor in transmission assets must have a tool to decide when and where to invest in new assets. One of the most important and frequent decisions managers have to make is the selection and optimization of new industrial projects. Most decision-making in capital budgeting follows the net present value (NPV) and interest rate of return (IRR) methods. Typically, the NPV and IRR methods can be applied in making a decision and relevant conditions are assumed to be static and certain.

The proposed model in the article estimated the optimal number of wind turbines in wind farm for the maximal net profit of the project investment. The impact of the number of turbines installed in the wind farm on the net profit of the wind farm has been investigated. As the parameters for measuring net profit of the wind farm NPV and IRR has been used. Hence, the study successfully, reached the optimal solution for the maximum net profit, at the maximum power production with an improved efficiency value of wind farm and also the optimal layout for the configuration of the wind turbines micro-siting is proposed. The placement is proposed with utilizing the maximum land of the available terrain keeping in view the fact that the minimal wake interaction occurred between turbines. An intelligent optimization procedure has been suggested. The ANFIS optimizer has been applied in order to find a maximum net profit value for a wind farm. This method is based on the regulation of the number of wind turbines installed in wind farm. As the parameters for measuring the net profit of the wind farm NPV and IRR has been used. A Simulink model has been developed in MATLAB with the ANFIS optimizer. Simulations were run in MATLAB and the results have been observed on the corresponding output blocks. The main advantages of the ANFIS scheme are: computationally efficient, well-adapted with optimization and adaptive techniques. The developed strategy is not only simple, but also easy to implement in real time applications using some interfacing cards like the DSPACE, data acquisition cards, NI cards, etc. for control of various parameters. This can also be combined with expert systems and rough sets for other applications.

Future investigations should lead to mobile networks of wind turbines [70,71]. The wind turbine mobile networks should be enabled to change their positions according to the optimal environmental wind conditions. The mobile wind farm networks should have embedded intelligence or cloud computing [72–75] which would enable active communication between all the wind turbines installed in the wind farms. The mobile wind farm networks with embedded intelligence should act according the environmental conditions.

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