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Adaptive Neuro-Fuzzy Optimization of the Net Present Value and Internal Rate of Return of a Wind Farm Project under Wake Effect

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Abstract

A wind power plant which consists of a group of wind turbines at a specific location is also known as a wind farm. The engineering planning of a wind farm generally includes critical decision-making regarding the layout of the turbines in the wind farm, the number of wind turbines to be installed, and the types of wind turbines to be installed. Two primary objectives of optimal wind farm planning are to minimize the cost of energy and to maximize the net energy production or to maximize wind farm efficiency. The optimal wind turbine placement on a wind farm could be modified by taking economic aspects into account. The net present value (NPV) and internal rate of return (IRR) are two of the most important criteria for project investment estimation. The general approach in determining the accept–reject–stay in the different decisions 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. To assess the investment risk of a wind power project, this paper constructed a process which initially simulated maximal NPV with the adaptive neuro-fuzzy inference system (ANFIS) method and then evaluated the IRR based on it. Subsequently, ANFIS simulated maximal IRR and then evaluated the NPV based on it. ANFIS showed very good learning and prediction capabilities, which makes it an efficient tool to deal with encountered uncertainties in any system. The aim of this paper is to develop a model to determine economically optimal layouts for wind farms which include the aerodynamic interactions between the turbines, the various cost factors, and the wind regime.

Keywords: Wind farm, ANFIS, wake effect, net present value (NPV), internal rate of return (IRR)

JEL Classification codes: F16, F21, F23, J51, L13

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The world's fastest growing renewable energy source is the wind energy. Wind turbines are machines which convert the wind energy into electricity (Yang, Sarkar, & Hu, 2011). A wind farm contains a number of horizontal wind turbines (Grant et al., 2000); these wind turbines are positioned and aligned in clusters facing the wind direction. Each wind rotor generates a turbulent region called *wake* (González-Longatt, Wall, & Terzija, 2012; Thomsen & Sørensen, 1999). 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 (Wagner, Day, & Neumann, 2013; Pookpunt & Ongsakul, 2013; Ituarte-Villarreal & Espiritu, 2011). While dense configurations appear as a good solution, the wake effect is a known side-effect of the tight spacing of the turbines (Eroglu & Seçkiner, 2013). It is caused by the fact that, when extracting energy from the wind, each turbine creates a cone of more turbulent and slower air behind it and, hence, the wind speed encountered by the downstream wind turbines decreases, leading to reduced energy yield (Mo, Choudhry, Arjomandi, Kelso, & Lee, 2013; Bartl, Pierella, & Sætran, 2012; Adaramola & Krogstad, 2011).

The optimal wind turbine placement on a wind farm could be modified by taking economic aspects into account. The conceptual design of a new wind farm involves the evaluation of alternative farm configurations to determine physical and economic feasibilities. In testing alternatives, designers require an absolute economic measure and a normalized economic measure in order to make a definitive evaluation. In recent years, Net Present Value (NPV) (Lin, 2009; Mellichamp, 2013; Keswani & Shackleton, 2006; Law, 2004; Schmit, Luo, & Tauer, 2009) has often been chosen as the absolute metric and Internal Rate of Return (IRR) (Cuthbert & Cuthbert, 2012; Talavera, Nofuentes, Aguilera, & Fuentes, 2007; Pichl, Kaizoji, & Yamano, 2007) as the normalized one.

The NPV and IRR are two of the most important criteria for choosing among investment projects (Brown & Kwansa, 1999; Pasqual, Padilla, & Jadotte, 2013). In many circumstances, investment projects are ranked in the same order by both criteria. Li, Lu, and Wu (2013) considered NPV and IRR as indexes to evaluate the investment risk of a wind power project. Vuccina, Lozina, and Vlak (2010) presented an alternative approach to a conceptual design, where a compound objective function based on the NPV and IRR aggregates the performance metrics. In some situations, however, the two criteria provide different rankings (Osborne, 2010). A difference between rankings implies inconsistent recommendations about a "best project". This inconsistency gives rise to a debate in the literature in regard to which criterion is superior. In Talavera, Nofuentes, and Aguilera (2010) and Percoco and Borgonovo (2012), sensitivity analyses of the IRR to some economic factors were carried out. Percoco and Borgonovo (2012) provided some evidence in support of the contention that the results of sensitivity analysis on NPV and IRR may differ substantially. Bidard (1999) showed that the maximum rate of growth and the minimum rate of interest are both equal to the IRR. Gardiner and Stewart (2000) proposed that investment appraisal techniques and NPV can and should be used as an ongoing monitor of project health. Naim, Wiknerb, and Grubbström (2007) showed the impact of using the NPV on parameter selection in the ordering policy of a production planning and control system.

In an uncertain economic environment, it is usually difficult to accurately predict the investment outlays and annual net cash flows of a project (Zhang, Huang, & Tang, 2011). In addition, the available investment capital sometimes cannot be accurately given either (Giri & Dohi, 2004). The general approach in determining the accept–reject–stay in the different decisions for a project via investment appraisal techniques, such as NPV and IRR, is to treat the cash flows as known with certainty (Bas, 2013; Gollier, 2010). However, even small deviations from the predetermined values may easily invalidate the decision (Hanafizadeh & Latif, 2011). Thus, redefined decision rules of investment appraisal techniques by considering the uncertainty in cash flows are indispensable for a reliable decision (Chen, Hung, & Weng, 2007; Holopainen et al., 2010). For this aim, in some approaches, it would be possible to consider the uncertainty in cash flows, such as in the fuzzy approach and robust approach (Huang, 2008; Huang, 2007). Wiesemann, Kuhn, and Rustem (2010) 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. Garcia, Contreras, Correia, and Muñoz (2010) 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.

For investors, project risks and the long-term positive trend are coexistent due to the joint influence of several factors, as the result of wind power industry circumstance and relative policies and regulations. The objective of the present study is to analyze the relationship between wind farm parameters and NPV and IRR criteria for project investment purposes. Aiming at optimizing such systems (Shiraz, Gani, Hafeez, & Buyya, 2012; Anuar, Sallehudin, Gani, & Zakari, 2008; Mansoori, Zakaria, & Gani, 2012; Enayatifar, Sadaei, Abdullah, & Gani, 2013) to ensure optimal investment in the wind farm, the adaptive neuro-fuzzy inference system (ANFIS) method is used (Mohandes, Rehman, & Rahman, 2012; Ata, Kocyigit, & Kocyigit, 2010; Jang, 1993; Shamshirband, Anuar, Kiah, & Patel, 2013).

This paper constructed a process which initially simulated the maximal NPV with ANFIS method. Then, IRR was evaluated based on this method in order to assess the investment risk of a wind power project. Subsequently, ANFIS simulated the maximal IRR and then evaluated the NPV based on it. ANFIS showed very good learning and prediction capabilities, which makes it an efficient tool to deal with encountered uncertainties in any system. ANFIS, as a hybrid intelligent system that enhances the ability to automatically learn and adapt, was used by researchers in various engineering systems (Al-Ghandoor & Samhouri, 2009; Singh, Kianthola, & Singh, 2012; Petković, Issa, Pavlović, Zentner, & Ćojbašić, 2012; Petković, Issa, Pavlović,

Pavlović, & Zentner, 2012; Kurnaz, Cetin, & Kaynak, 2010; Tian & Collins, 2005). Thus far, there are many studies of ANFIS application for estimation and real-time identification of many different systems (Bektas Ekici & Aksoy, 2011; Khajeh, Modarress, Rezaee, 2009; Inal, 2008; Lo & Lin, 2005; Khalifehzadeh, Forouzan, Arami, & Sadrnezhaad, 2007; Vairappan, Tamura, Gao, & Tang, 2009; Han, Zeng, Zhao, Qi, & Sun, 2011; Karaagac, Inal, & Deniz, 2011; Zhang & Friedrich, 2003).

The objective function of NPV and IRR for the total relevant costs considered in our model is mathematically formulated. A complete search procedure is provided to find the optimal solution by employing the properties derived in this paper and the ANFIS algorithm. The aim of this paper is to develop a model to determine economically optimal layouts for wind farms (number of turbines and their locations), which include the aerodynamic interactions between the turbines (wake effect), the various cost factors, and the particular wind regime.

Wind Farm

The aim of this paper is to analyze a wind farm model. By using the model, the optimal layout can be determined by maximizing the expected NPV and/or IRR. In this study, a rectangular grid wind farm layout (Figure 1) of ixj wind turbines of equal size and height is considered. The optimizing procedure should determine distances (x, y) between wind turbines for a different number of rows and columns (i, j) of wind turbines in the wind farm.

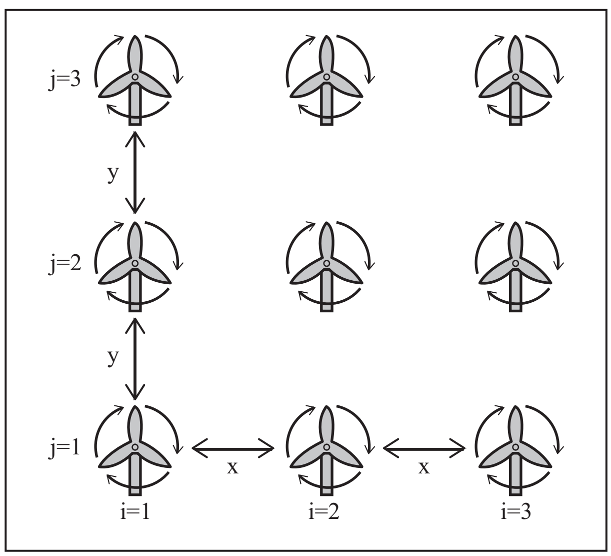

Figure 1. Location of turbine i, j in a rectangular grid layout of ixj wind turbines.

Aerodynamic Interaction between Wind Turbines

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 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, the analytical wake model named as *Jensen's wake model* (Jensen, 1983) is chosen, because momentum is considered as conserved inside the wake by this model. The wake expands linearly with downstream distance. Therefore, this model is suitable for the far wake region. The wake has a radius, at the turbine which is equal to the turbine radius R_r, while R_1 is the radius of the wake in the model. R_1 is considered as the radius of the downstream wake; the relationship between R_1 and X is the downstream distance when the wake spreads downstream the radius R_1, that increases linearly proportional, X. The wake expands linearly with the downstream distance, as stated in Jensen's model as shown in Figure 2.

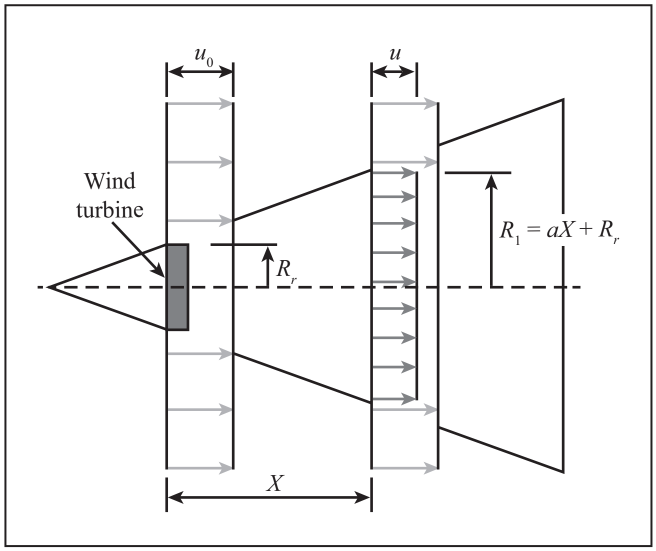

Figure 2. Schematic of analytical wake model.

Equation 1 is used to determine the wind speed after wind turbine rotor, as shown in Figure 2:

$$u = u_0 * \left(1 - \frac{2a}{1 + \alpha\left(\frac{X}{\left(R_r\sqrt{\frac{1-\alpha}{1-2\alpha}}\right)}\right)^2}\right). \tag{1}$$

In a windfarm, the turbine (i, j) 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. Equation 1 represents the complete wake effect of a wind turbine in front of another. An interesting state of the wake effect is when a portion of the turbine (i, j) is affected simultaneously by the wake of two wind turbines, as shown in Figure 3.

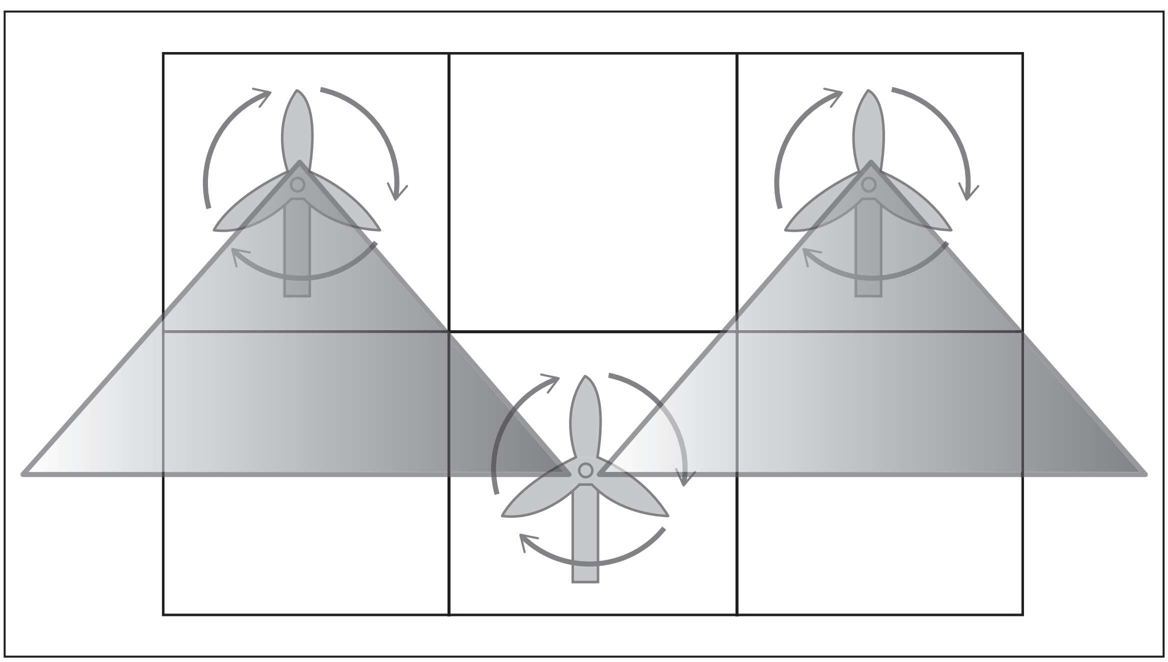

Figure 3. Multiple partial interference of the wake effects.

Equation 2 is used to determine the wind speed for multiple partial interference of the wake effects after the two wind turbine rotors, as shown in Figure 3.

$$u_{i+1} = u_i * \left(1 - \sqrt{\left(\frac{2a}{1+\alpha\left(\frac{X}{\left(R_r\sqrt{\frac{1-\alpha}{1-2\alpha}}\right)}\right)^2}\right)^2 + \left(\frac{2a}{1+\alpha\left(\frac{X}{\left(R_r\sqrt{\frac{1-\alpha}{1-2\alpha}}\right)}\right)^2}\right)^2}\right), \qquad (2)$$

where:

$i = 0, 1, \dots, N$.

In the Equations 1 and 2 we have:

- u_0 is the mean wind speed or what can be explained as the free stream wind speed. In this study, it was used $u_0 = 12$ m/s;
- Axial induction factor is denoted by a which can be calculated from the C_T, the thrust coefficient. This can be determined from the expression: $C_T = 4a(1 - a)$;
- X is considered as the distance downstream of the turbine, while R_1 is related to R_r as represented using the following equation: $R_1 = R_r\sqrt{\frac{1-a}{1-2a}}$; and
- α is the entertainment constant and it can be obtained by computing the following equation: $\alpha = \frac{0.5}{\ln\frac{z}{z_0}}$.

In the above equation, z is used to denote the hub height and the roughness of the surface is denoted by z_0. The value for surface roughness varies from field to field. For plain terrains, the value for $z_0 = 0.3$.

Figure 4 shows the wind velocity reductions after rotors in relation to the wind turbine position (row number) and for different combinations of the distances between the wind turbines and rotor radius. It is clear that the largest reduction of the wind speed after rotor is occurred for the smallest distances between the wind turbines.

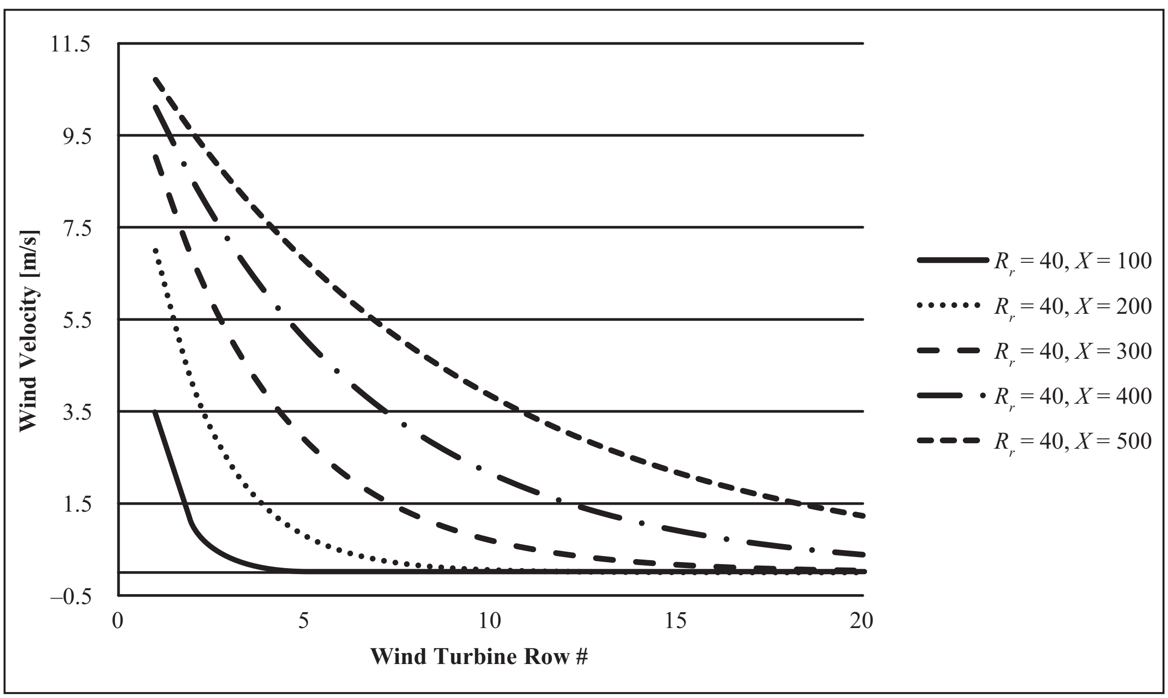

Figure 4. Wind velocity reduction in relation to wind turbine position in the wind farm layout, different distances between wind turbines for rotor or wake radius $R_r = 40$ *m*.

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: NPV and IRR.

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.

NPV 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 follows: NPV = Cash Inflows - 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. Assuming that you are considering a project that has cash flows CF_0, CF_1, CF_2, …, CF_n, and the appropriate discount rate for this project is r, then the NPV of the project is:

$$NPV = -CF_0 + \frac{CF_1}{(1+r)^1} + \frac{CF_2}{(1+r)^2} + \ldots + \frac{CF_n}{(1+r)^n} = -CF_0 + \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t}. \tag{3}$$

A project is worthwhile by the NPV rule if its $NPV > 0$. In this expression, CF_t represents the 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 from two mutually exclusive projects. Assume that you are trying to decide between two projects A and B where the same objective can be achieved. Project A has cash flows CF_0^A, CF_1^A, CF_2^A, … , CF_n^A, and project B has cash flows CF_0^B, CF_1^B, CF_2^B, … , CF_n^B. Project A is preferred to project B if:

$$NPV(A) = -CF_0^A + \sum_{t=1}^{n} \frac{CF_t^A}{(1+r)^t} > -CF_0^B + \sum_{t=1}^{n} \frac{CF_0^B}{(1+r)^t} = NPV(B). \tag{4}$$

The logic of both *NPV* rules presented above is that the PV of a project's cash flows represents the current economic value of the project.

$$PV = \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t}. \tag{5}$$

Thus, if we have correctly chosen the discount rate r for the project, the *PV* is what we ought to be able to sell the project for in the market. NPV is the wealth increment produced by the project, so that $NPV > 0$ means that a project adds to our wealth:

$$NPV = -CF_0 + \sum_{t=1}^{n} \frac{CF_t}{(1+r)^t}, \tag{6}$$

where CF_0 is the initial cash flow required to implement the project; this is usually a negative number. And $\sum_{t=1}^{n} \frac{CF_t}{(1+r)^t}$ is the market value of the future cash flows.

An alternative to using the NPV criterion for capital budgeting is to use the 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 what rate of return an investor is taking on a project. IRR provides the answer in percentage. It is actually based on the PV concept; the amount of money which you receive today has more worth than the one you receive tomorrow. IRR is essentially the capital budgeting technique that equates the NPV answer to the initial investment or cost. Two decision rules for using the IRR in capital budgeting are explained below.

IRR determines whether or not a specific investment is worthwhile. Suppose we are considering a project that has cash flows CF_0, CF_1, CF_2, … , CF_n. IRR is an interest rate such that:

$$-CF_0 + \frac{CF_1}{(1+IRR)^1} + \frac{CF_2}{(1+IRR)^2} + \ldots + \frac{CF_n}{(1+IRR)^n} = -CF_0 + \sum_{t=1}^{n} \frac{CF_t}{(1+k)^t} = 0. \tag{7}$$

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 which investment is providing a comparatively better rate of return. Some investors prefer to use IRR so as to make decisions 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 the rate of return rather than the actual money return. They tend to find NPV less intuitive because it does not measure the amount relative to the amount invested. Nevertheless, some investors prefer to use the NPV because it evaluates the investment project in amount. In amount or money value, it is easy to understand what a project is providing in return, but in IRR it is difficult to evaluate. Since IRR gives answers in percentage, in many cases it becomes difficult for investors to evaluate return. NPV project evaluation is superior to that of IRR. NPV discounts all the cash flows up to date to see whether the investment project will benefit or cause losses to the investor.

IRR determines which project will be accepted from two competing projects. 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, … , CF_n^A, and that project B has cash flows CF_0^B, CF_1^B, CF_2^B, … , CF_n^B. Project A is preferred to project B if:

$$\text{IRR(A)} > \text{IRR(B)}. \tag{8}$$

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. Table 1 shows NPV and IRR criteria for accepting or rejecting the projects and for the projects ranking.

Table 1
NPV and IRR Rules

NPV and IRR rules		
Criterion	Yes or No: Choosing whether or not to undertake a single project	Project ranking: Comparing two mutually exclusive projects
NPV criterion	The project should be undertaken if its NPV > 0	Project A is preferred to project B if NPV(A) > NPV(B)
IRR criterion	The project should be undertaken if its IRR > r, where r is the appropriate discount rate	Project A is preferred to project B if IRR(A) > IRR(B)

Optimization Problem

The available wind power of one wind turbine can be calculated by using Equation 9:

$$P_a = \tfrac{1}{2}\,\rho\, Au^3. \tag{9}$$

Assuming that the power production from each wind turbine contains the efficiency η of the wind turbine, then Equation 10 can be used for the energy or power generated from a wind turbine:

$$P_p = \eta\, \tfrac{1}{2}\,\rho\, Au^3. \tag{10}$$

Assuming that the efficiency of wind turbines is equal to 40%, then the equation will become:

$$P_p = \tfrac{40}{100}\,\tfrac{1}{2}\,\rho\, Au^3. \tag{11}$$

In Equation 11, A represents the cover surface of the turbine blades during rotation and it is $A = \pi\ 40^2$, since the used rotor radius in the study is $R_r = 40\ m$, and $\rho = 1.2$. Equation 12 will be derived:

$$P_p = 301\ u^3\ W. \tag{12}$$

For the calculation of power into kW we have Equation 13:

$$P_p = 0.3\ u^3\ kW. \tag{13}$$

The total extracted power from all wind turbines in the wind farm can be expressed as:

$$P_t = \sum\nolimits_{i=1}^{N_t} 0.3 \times u_i^3\ kW. \tag{14}$$

NPV of the profit to be derived from the farm is:

$$NPV = -CF_0 + \sum\nolimits_{t=1}^{n} \frac{T * P_t * C - M}{(1+r)^t} = -CF_0 + \sum\nolimits_{t=1}^{n} \frac{CF_t}{(1+r)^t}, \tag{15}$$

where CF_0 represents the total investment in the wind farm (cost of turbines, installations, and land cost), CF_t 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, P_t is the total extracted power from all wind turbines in the wind farm, C is the unit sale price of electricity, and M is the cost of operation and maintenance of the wind farm per period.

The IRR of the investment is the value of the interest rate r, that results in $NPV = 0$.

In this study, the values used for different variables are as follows:

$X = 200\ m$;

$R_r = 40\ m$;

$u_0 = 12\ m/s$;

$a = 0.326795$;

$\alpha = 0.09437$;

$T = 7{,}884$ hours/year;

$C = 0.05$ \$/kWh;

$CF_0 = i * j * (CT + CI + CL * ((i - 1) * x * (j - 1) * y))$;

CT = cost per turbine;

CI = cost per turbine installation;

CL = cost of land per turbine;

$M = 0.015 * CT * i * j$.

Two optimization problems are defined. The optimization variables are distances between the wind turbines. The first problem maximizes NPV and calculated IRR based on the maximal NPV:

$\max[NPV1(x, y)]$;

$\max[NPV1(x, y)] = 0 \rightarrow IRR1(x, y)$;

$100\,m < x < 500\ m$;

$100\,m < y < 500\ m$.

The second optimization problem maximizes IRR and calculated NPV based on the maximal IRR:

$\max[IRR2(x, y)]$;

$\max[IRR2(x, y)]\ 0 \rightarrow NPV2(x, y)$;

$100\,m < x < 500\ m$;

$100\,m < y < 500\ m$.

Neuro-Fuzzy Computing

Soft computing is an innovative approach in the construction of systems that are computationally intelligent and possess human-like expertise within a specific domain. These systems are supposed to adapt in changing environments, learn to perform better, and explain their decision making process. It is usually more beneficial to employ several computing methods in a synergistic way rather than building a system based exclusively on only one technique. This is useful in confronting real-world computing problems. The result of such synergistic use of computing techniques is the construction of complementary hybrid intelligent systems. The epitome of designing and constructing intelligent systems of this kind is neuro-fuzzy computing: firstly, neural networks recognizing patterns and adapting to cope with evolving environments; and secondly, fuzzy inference systems that include human knowledge and implement decision making and differentiation. The combination and integration of these two complementary methodologies produces a novel discipline called *neuro-fuzzy computing*.

Adaptive Neuro-Fuzzy Inference System

Fuzzy Inference System (FIS) is the main core of ANFIS. 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. The advantage of FIS is that it does not require knowledge of the underlying physical process as a precondition 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 that 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; they adapt themselves and learn to do better in changing environments. In ANFIS, neural networks recognize patterns and help the adaptation of environments. ANFIS is tuned with a back propagation algorithm based on the collection of input-output data.

The ANFIS model will be established in this study to estimate the maximal NPV and maximal IRR of the wind farm, i.e., the ANFIS networks should determine the optimal distances between turbines for a given number of turbines "ixj". Fuzzy logic toolbox in MATLAB was used for the entire process of training and evaluation of the fuzzy inference system. Figure 5 shows an ANFIS structure with three inputs.

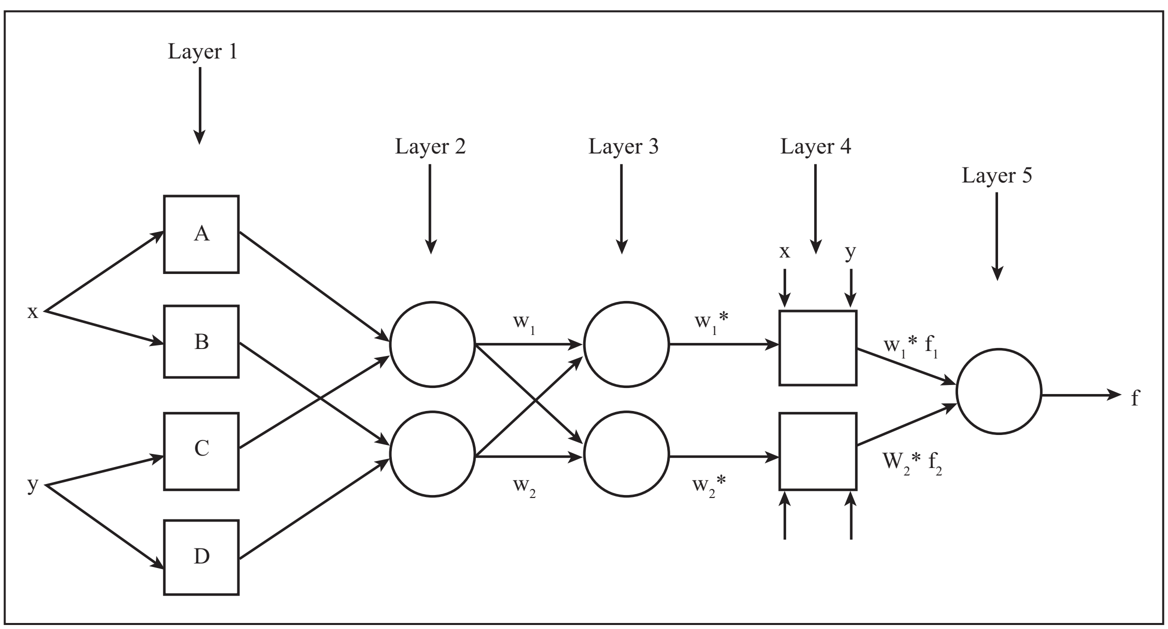

Figure 5. ANFIS structure.

In this work, the first-order Sugeno model with two inputs and fuzzy If-Then rules of Takagi and Sugeno's type is used:

if x is A and y is C and z is E, then $f_1 = p_1 x + q_1 y + r_1 z + t$. (16)

The first layer consists of input variables MFs, input 1 and input 2. This layer just supplies the input values to the next layer. Input 1 is the number of turbines in i direction (number of columns). Input 2 is the number of turbines in j direction (number of rows). In the first layer, every node is an adaptive node with a node function: $0 = \mu(x, y, z)$, where $\mu(x, y, z)_i$ are MFs.

In this study, bell-shaped MFs (3) with maximum equal to 1 and minimum equal to 0 are chosen:

$$f(x; a, b, c) = \frac{1}{1+\left(\frac{x-c}{a}\right)^{2b}}, \tag{17}$$

where the bell-shaped function depends on three parameters a, b, and c. The parameter b is usually positive. The parameter c is located in the center of the curve, as shown in Figure 6.

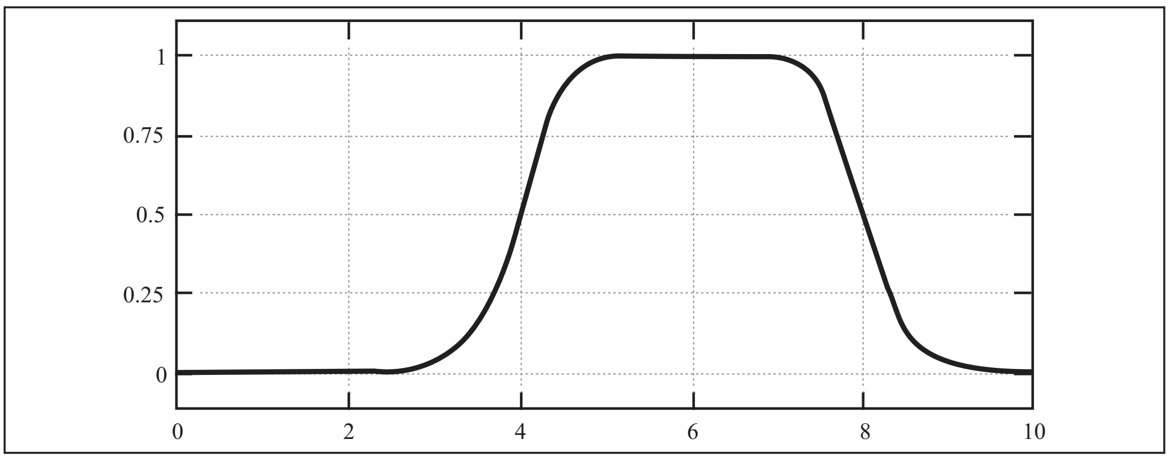

Figure 6. Bell-shaped membership function (a = 2, b = 4, c = 6).

The second layer (membership layer) checks for the weights of each MF. It receives the input values from the first 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 as follows:

$$w_i = \mu(x)_i * \mu(x)_{i+1}. \tag{18}$$

Each output node 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 precondition 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 that 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 as follows:

$$w_i^* = \frac{w_i}{w_1 + w_2}, \tag{19}$$

where $i = 1, 2$.

The outputs of this layer are called normalized firing strenghts 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 the following node function:

$$O_i^4 = w_i^* xf = w_i^* (p_i x + q_i y + r_i), \tag{20}$$

where $\{p_i, q_i, r\}$ 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 the 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.

$$O_i^4 = \sum_i w_i^* \, x \, f = \frac{\sum_i w_i f}{\sum_i w_i}. \tag{21}$$

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

Results

Figure 7a and 7b show the ANFIS root mean square (ANFIS RMS) errors during the training procedure to maximize the NPV criterion. Figure 7a represents the root mean square error (RMSE) for x-distance between turbines. Figure 7b represents the RMSE for y-distance between turbines.

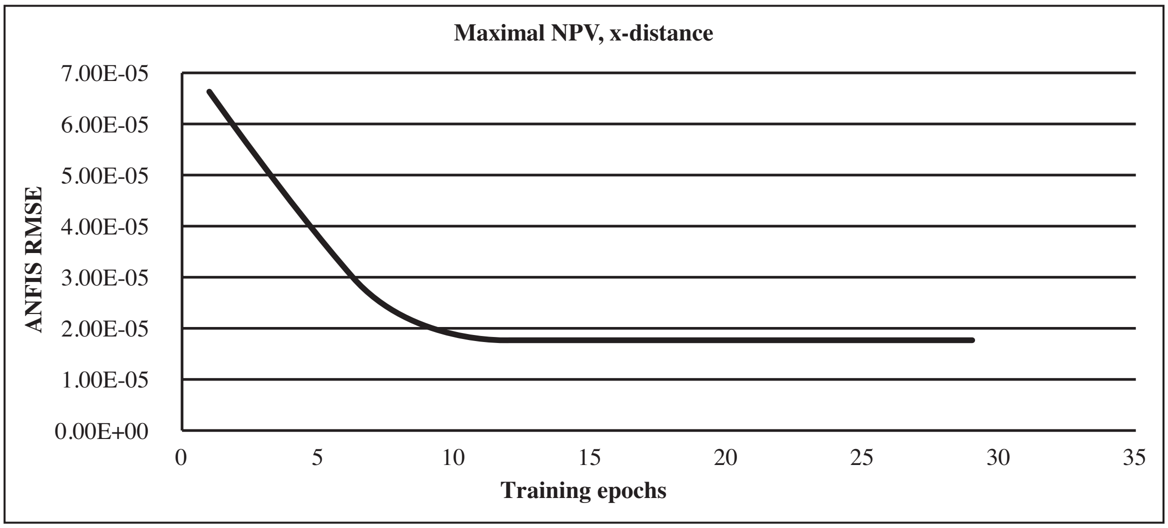

Figure 7a. ANFIS RMS errors during the training procedure to maximize the NPV: RMSE for x-distance between turbines, RMSE = 0.0000176439.

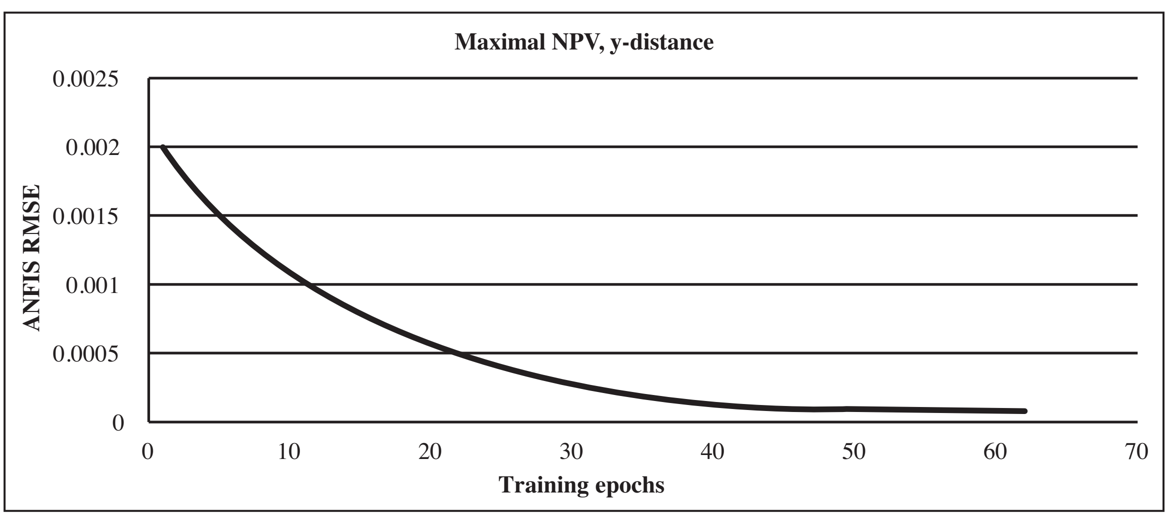

Figure 7b. ANFIS RMS errors during the training procedure to maximize the NPV: y-distance between turbines, RMSE = 0.000078453.

Figure 8a and 8b show the ANFIS RMS errors during the training procedure to maximize the IRR criterion. Figure 8a represents the RMSE for x-distance between turbines. Figure 8b represents the RMSE for y-distance between turbines.

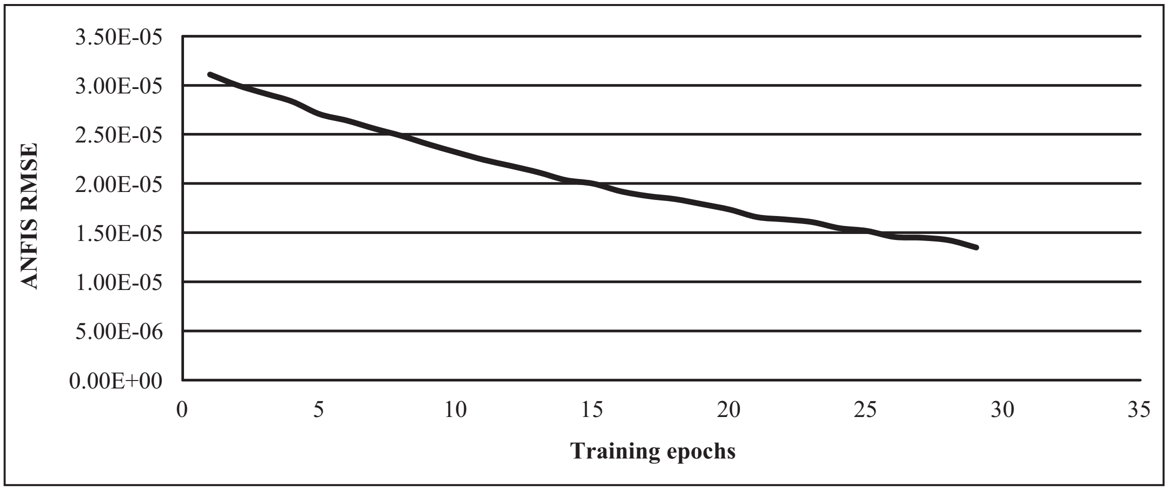

Figure 8a. ANFIS RMS errors during the training procedure to maximize the IRR: x-distance between turbines, RMSE = 0.000013487.

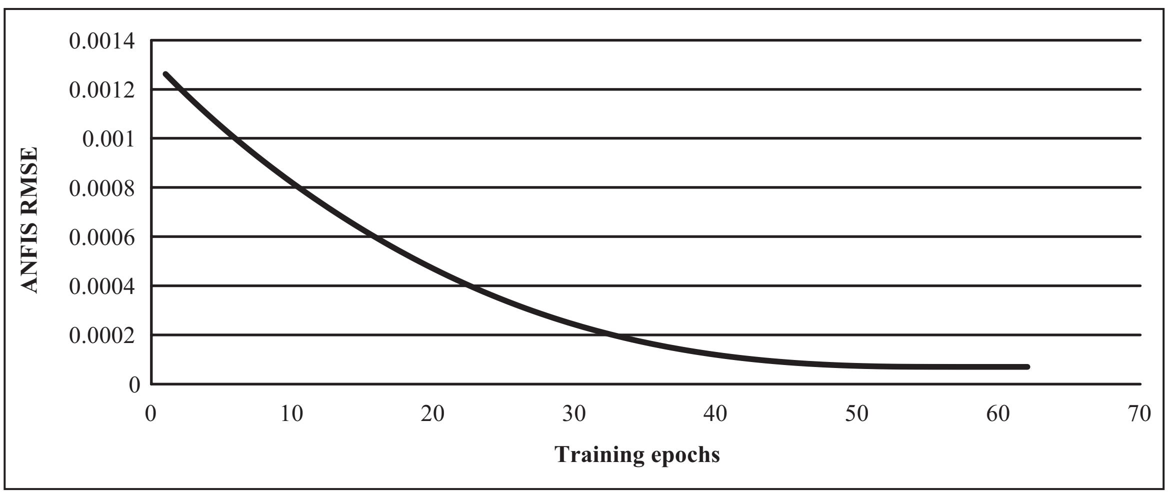

Figure 8b. ANFIS RMS errors during the training procedure to maximize the IRR: y-distance between turbines, RMSE = 0.0000697382.

Figure 9 and Figure 10 show the ANFIS predicted relationships between the number of wind turbines (i, j: number of columns and rows) and the distances (x, y) between turbines for maximal NPV criterion. Therefore, the ANFIS networks determine the optimal distances between turbines in the wind farm which leads to the maximal NPV of the farm.

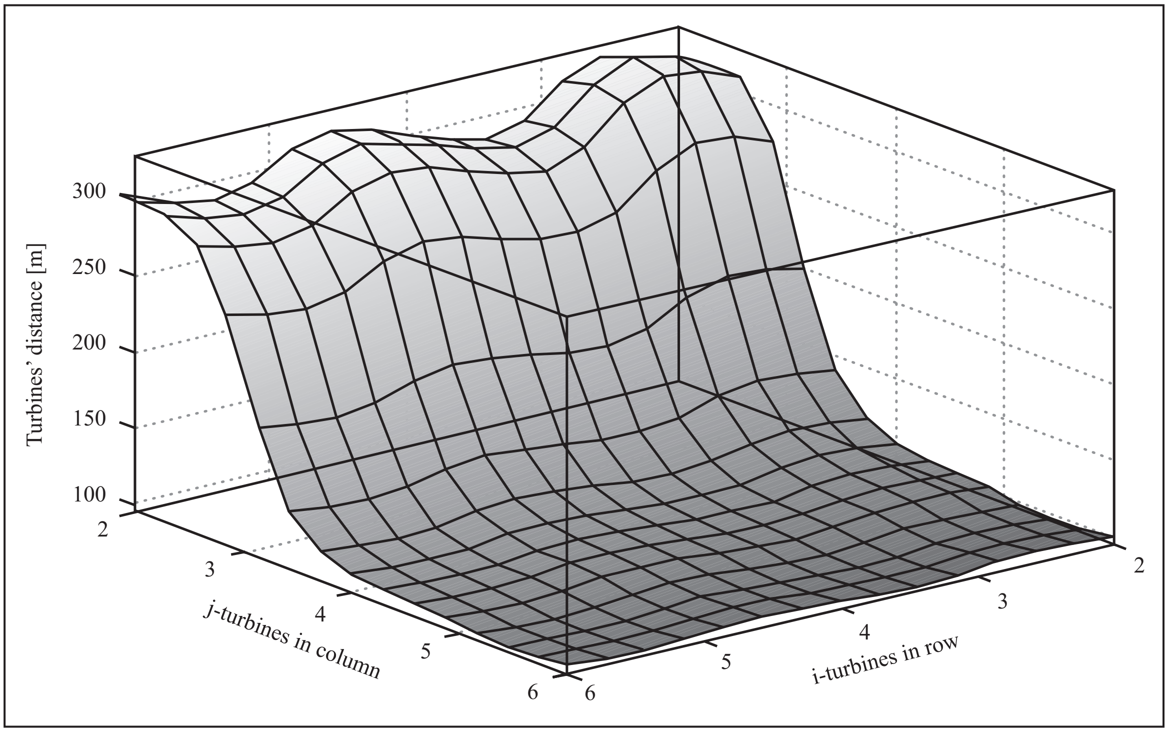

Figure 9. ANFIS predicted relationship between the number of turbines (i, j: number of columns and rows) and the optimal distances between turbines in x-direction for maximal NPV.

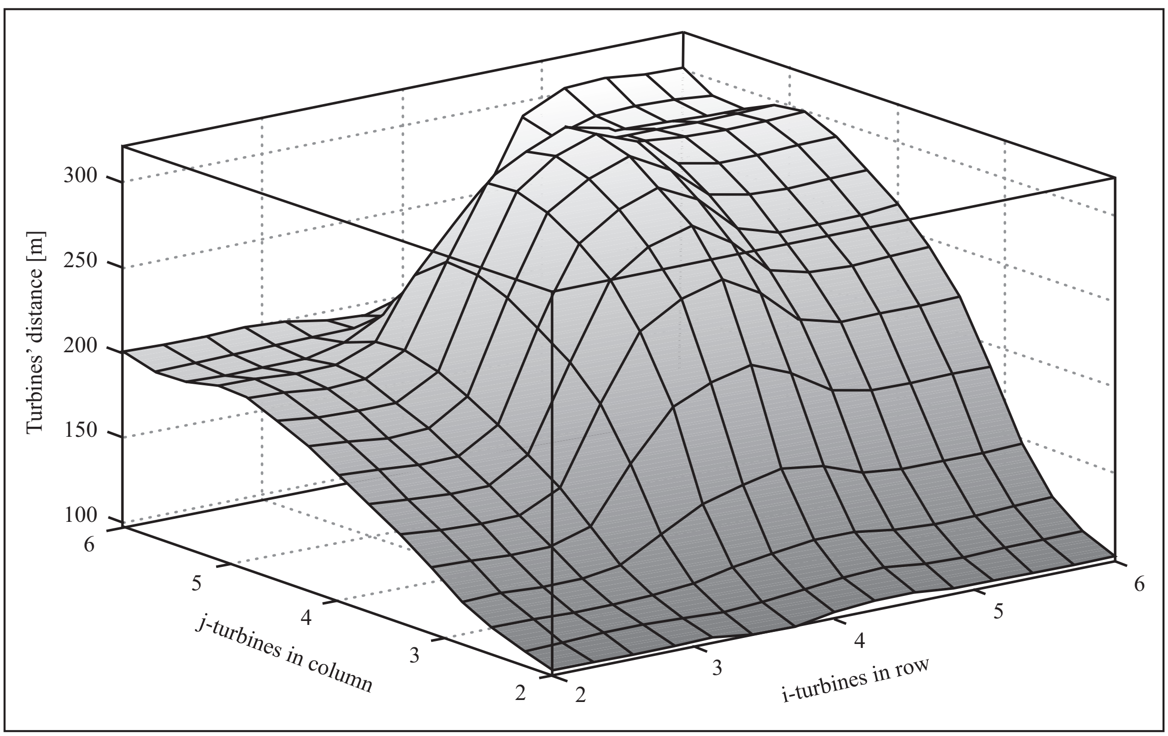

Figure 10. ANFIS predicted relationship between the number of turbines (i, j: number of columns and rows) and the optimal distances between turbines in y-direction for maximal NPV.

Figure 11 and Figure 12 show the ANFIS predicted relationships between the number of wind turbines (i, j: number of columns and rows) and the distances (x, y) between turbines for maximal IRR criterion. Therefore, the ANFIS networks determine the optimal distances between turbines in the wind farm which leads to the maximal IRR of the farm.

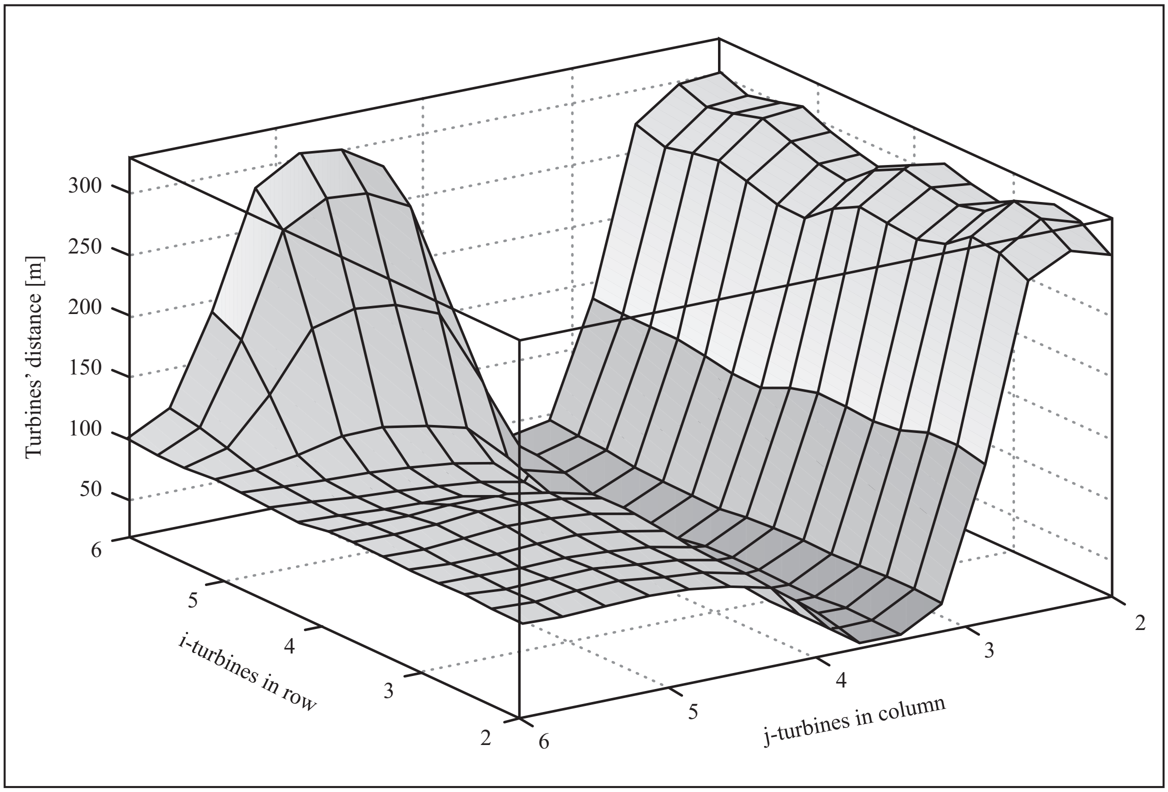

Figure 11. ANFIS predicted relationship between the number of turbines (i, j: number of columns and rows) and the optimal distances between turbines in x-direction for maximal IRR.

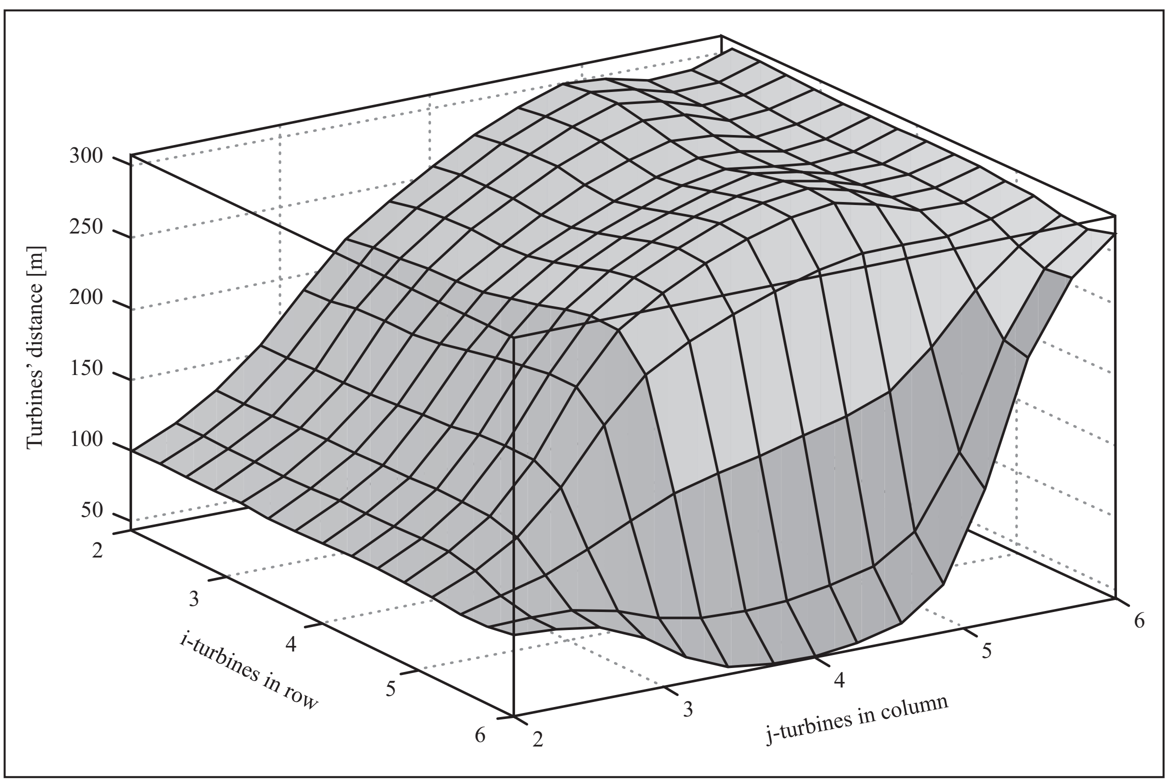

Figure 12. ANFIS predicted relationship between the number of turbines (i, j: number of columns and rows) and the optimal distances between turbines in y-direction for maximal IRR.

The optimal distances (x, y) between turbines as a function of the number of wind turbines (i, j: number of columns and rows) are implemented in the MATLAB Simulink block diagram, as shown in Figure 13. As it can be seen, there are two blocks of the block diagram. One block maximizes the NPV and one block maximizes the IRR of the proposed number of columns and rows of the turbines in the wind farm. For instance, we can notice different result for 5x5 wind turbines. For maximal NPV of the farm of 5x5 turbines, the optimal distance in x-direction is 100 m and in y-direction is 500 m. The maximal NPV1 for this farm layout is 21.9 million dollars and the appropriate financial interest rate IRR1 is 17.2%. On the contrary, for maximal IRR of the farm layout of 5x5 turbines the optimal distance in x-direction is 100 m and in y-direction is 300 m. The maximal IRR2 for this farm layout is 19% and the appropriate net present value NVP2 is 21.4 million dollars. The project investors should decide in which directions they should go. This approach is very useful for a fast estimation of the main investment parameters of wind farms according to the number of installed wind turbines.

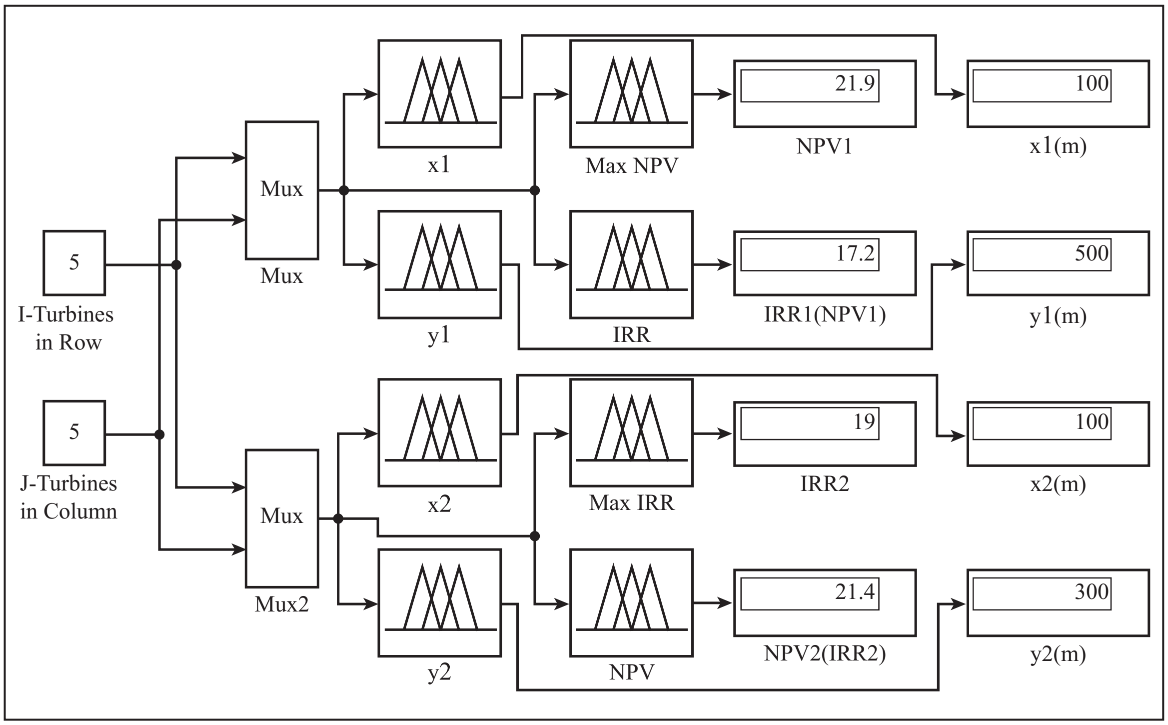

Figure 13. Simulink block diagram for the estimation of the optimal distances (x, y) of the turbines for maximizing NPV and IRR of the wind farm.

Conclusion

In a wind farm, space and economic constraints make it impossible to locate turbines sufficiently far apart to prevent interactions between them. The effect of these interactions may have severe implications on the downstream turbines located in the wake of the upstream ones. The turbine wake is characterized by stream wise (axial) velocity deficit, which leads to less power available for the downstream turbines. It also causes high turbulence levels which can give rise to high fatigue loads.

The developed model in the article optimizes wind farm layouts for both economic and aerodynamic criteria. Although there are other criteria to consider, the model performance is an advance for economic optimization. In an uncertain economic environment, experts' knowledge about outlays and cash inflows of available projects consists of much vagueness instead of randomness. Investment outlays and annual net cash flows of a project are usually predicted by using experts' knowledge. Fuzzy variables can overcome the difficulties in predicting these parameters. In this study, a systematic approach to achieving the maximal NPV internal rate of return of wind farm by means of the ANFIS strategy was investigated. A Simulink model was developed in MATLAB with the ANFIS network for NPV and IRR estimation. The main advantage of designing the ANFIS coordination scheme is to estimate the most important economic parameter as a very important criterion for overall wind farm project investment. Simulations were run in MATLAB and the results were observed on the corresponding output blocks.

The main advantages of the ANFIS scheme are: it is computationally efficient, well-adaptable with optimization, and counts with adaptive techniques. ANFIS can also be used with systems handling more complex parameters. Another advantage of ANFIS is its speed of operation, which is much faster than in other control strategies. Furthermore, the tedious task of training MFs is done in ANFIS.

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