IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 20 September 2023, accepted 11 October 2023, date of publication 16 October 2023, date of current version 25 October 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3324884

RESEARCH ARTICLE

Optimal Wind Turbine Design Based Wind Potential and Radial Distribution Network Characteristics

FATIMA-AZAHRAA BOURHIM[1], AHMED OUAMMI[2], RACHID BENCHRIFA[1], AND MOHAMED CHAOUCH[3]

[1]Laboratory of Condensed Matter and Interdisciplinary Sciences, Faculty of Sciences, Mohammed V. University, Rabat 1014, Morocco
[2]Department of Electrical Engineering, École de Technologie Supérieure, Montreal, QC H3C 1K3, Canada
[3]Program of Statistics, Department of Mathematics, Statistics and Physics, College of Arts and Sciences, Qatar University, Doha, Qatar

Corresponding author: Mohamed Chaouch (mchaouch@qu.edu.qa)

This work was supported by the Qatar National Library.

ABSTRACT This paper aims to present an economic decision-making model for determining the optimal wind turbine (WT) design for different bus nodes in a Radial Distribution Network (RDN) based on the wind potential of the studied site and grid capability. The main objective function in the optimization problem of this study is the maximization of the Net Present Value (NPV) of wind energy incomes subject to the WT geometrical design variables, including the rotor diameter and Tower Height; and under the RDN constraints to maintain the power system stability. Adequate placements among the different bus nodes for WT installation are those with the maximum NPV value. Furthermore, the intermittent characteristic of wind energy leads to the use of an Artificial Neural Network (ANN) in wind speed forecasting for good estimation of the generated wind energy. The effectiveness of the proposed model was validated using IEEE 9 and IEEE 33 Bus RDNs. The results demonstrate that the WT design determination is not related to the power of the wind potential but mostly to the capability of the connected RDN.

INDEX TERMS Artificial neural network, NPV, optimization, radial distribution network, wind energy, wind turbine.

NOMENCLATURE

ANN	Artificial Neural Network.
NPV	Net Present Value.
RDN	Radial Distribution Network.
WT	Wind Turbine.
$f(z)$	Sigmoid function.
w	Weight associated with the ANN input.
R	Regression coefficient.
MSE	Mean Square Error.
N	The number of wind speed samples.
$v_{mes,i}$	The measured wind speed.
$v_{pred,i}$	The predicted wind speed.
$\overline{v_{mes,i}}$	The actual mean measured wind speed.
$\overline{v_{pred,i}}$	The actual mean predicted wind speed.
$E^l_{t,g}$	The yearly generated energy.
g	WT technology index.
l	The bus nodes location.
ρ	The air density(kg/m3).
S_g	The WT Rotor swept surface.
$f^l_{i,h}$	The discretized Weibull function.
k^l	Weibull shape parameter.
C^l(m/s)	Weibull scale parameter.
$C_{p,i,g}$	The total efficiency of the WT technology g.
v_i	The wind speed of the ith class.
D_g	The Rotor diameter (m) of WT technology g.
H_g	Tower hub height of WT technology g.
$\overline{\eta_{gear,i,g}}$	The WT gearbox efficiency.
$\overline{\eta_{gen,i,g}}$	The WT generator efficiency.
$C_{pr,i,g}$	The rotor power coefficient of the WT technology g.
$C^{max}_{pr,g}$	The Rotor maximum power coefficient.

The associate editor coordinating the review of this manuscript and approving it for publication was Mostafa M. Fouda.

$v_{p,g}$	The optimal wind speed.
χ	The Wind speed operating range parameter.
$v_{n,g}$	The nominal Wind speed of WT.
$\lambda_{max,g}$	The maximum speed rate.
BN_g	The number of blades.
c_d/c_l	The ratio between drag and lift coefficients.
ω_g	The angular rotation speed of the Rotor.
$N_{rpm,g}$	The Rotor rotation speed (rpm).
$\phi_{gear,g}$	The gearbox efficiency factor.
$\phi_{gen,g}$	The generator efficiency factor.
$P_{n,g}$	The WT nominal power.
$P_{p,g}$	The WT optimal power.
$P_{r,i,g}$	The Rotor power captured.
$P_{gear,i,g}$	The WT gearbox generated power.
$P_{n,gen}$	The WT generator nominal power.
$F_{s,g}$	The factor of service of the gearbox.
α	The generated WT energy losses.
$E^l_{t,g,real}$	The real yearly generated energy.
$I^l_{t,g}$	The Investment made in year t ($).
$C^{Net,l}_{benif,t,g}$	The total net Wind energy generation benefices.
$C^l_{benif,t,g}$	The total benefits.
$C^l_{OM,t}$	The Operation and Maintenance costs in year t ($).
$D^l_{t,g}$	The annual depreciation expense ($).
$T^l_{t,g}$	Tax levy ($).
n	The WT lifetime.
r	The Discount rate.
$C^{benif,l}_{Sal,t,g}$	The Incomes from electrical energy sales.
$C^{benif,l}_{Inc,t,g}$	The Incomes from incentives for green energy production.
C_S	The purchase tariff of electricity.
C_{In}	Sales cost due to incentives for green energy production.
η, ξ	The investment and incomes percentages factors.
$C^l_{T,g}$	The Transportation cost.
$C^l_{AI,g}$	The Assembly and Installation cost.
$C^l_{EI,g}$	The Electrical Interface cost.
$C^l_{EP,g}$	The Engineering and Permits cost.
$C^l_{RCW,g}$	The Roads and Civil Work cost.
$C^l_{F,g}$	The Foundation cost.
$C^l_{WT,g}$	The WT cost.
$P^l_{WT,g}$	The WT generated active power.
P^l_{Load}	The load active power.
P^l_{Loss}	The power losses in the branches lines of the radial distribution system.
V_l, V_j	The Voltage magnitudes at bus l and j.
G_{lj}	The real part of admittance matrix.
B_{lj}	The imaginary part of admittance matrix.
δ_l, δ_j	Voltage angles at buses l and j.
M	The number of buses.

I. INTRODUCTION

The effects of climate change are increasingly harming the planet. The earth's temperature is growing. Fossil fuel costs rise every day, especially after the Ukrainian-Russian crisis. Potable water and energy crises are major problems that have led the world to be united to fight these issues. Renewable energy is the mean alternative source of energy that should be used to meet electrical needs. Wind energy is the most competitive source of energy studied and integrated into power systems. The penetration of this source as a distributed generator in the distribution network of the power system poses many challenges related to voltage stability, power losses, and the quality of distributed power [1]. Voltage stability may extend to the transmission system and cause a power cut in the entire system [2]. An inappropriate size and placement may increase system losses [3]. Furthermore, inappropriate design of WTs may not profit from the maximum available wind energy at the studied site and may lead to high costs. To deal with these issues for optimal operation and maintaining the stability of the power system, there is a necessity for a decision making model to optimally size Wind Turbines (WTs) for different load buses in the distribution network, including wind profile and grid constraints that present good economic benefits.

This paper proposes an economic decision-making model that provides an adequate design of WT technical parameters, including rotor diameter D_g, Tower Hub Height H_g, and its nominal power, corresponding to the available wind potential at the site of interest and to the distribution network technical characteristics, with the Net Present Value (NPV) of wind energy income maximization as an objective function. The efficiency of wind power plant generation depends first on good forecasting of the available wind potential. This study first focuses on wind speed prediction with minimum errors compared to the measured values using an Artificial Neural Network (ANN), which helps to improve the effectiveness of the estimated generated energy.

WT design optimization studies that provide the optimal diameter and tower height have been conducted by researchers. In [4], the best trade-off between tower hub height and blade length, which constitutes half of the rotor diameter, minimizing the cost of energy was studied in low-speed areas to optimize the WT design. The results showed that the impact of the tower hub height on reducing the energy cost was greater than that of the rotor diameter. Reference [5] involved a WT optimization problem at high-altitude sites, minimizing the cost of energy to determine the optimal WT technical parameters, including the rotor radius, tower hub height, and rated power. Multi-objective design optimization of WTs considering the altitude was also proposed in [6]. The design objectives studied were energy cost minimization and maximization of the rated power considering the rotor radius and tower height. They observed that when the altitude increased, the cost of energy increased, the rated power decreased, and the best WT design parameters were within the design limits. In this study, the WT-rated power was limited and maximized with respect to wind potential variation with altitude, but there was no evaluation of the RDN constraints. For the same objective of cost of energy minimization, [7] predicted the optimal WT tower hub height-to-rotor diameter ratio using an excel-based optimization program and a tested WT database. As WT-rated power maximization is a popular method for WT cost reduction, the technical feasibility and economic attractiveness of optimized up-scaling wind turbines with power capacities of 5, 10, and 20 MW were studied in [8] using a multidisciplinary design optimization technique. Tower and rotor was the design variables studied to minimize the levelized cost of energy. Results obtained showed that these WTs were technically feasible but their costs were expensive. These studies did not evaluate the integration of WTs in the distribution network; instead, optimal design parameters were provided. In addition, the economic attraction is not limited to the low cost of energy but mostly to the NPV economic benefits of the WT designs involved, which constitute the interests of our research.

The remaining literature found that treating WT design parameter optimization mainly D_g, H_g, and nominal power, a single WT design parameter optimization constituted the interest of some researchers, mainly tower height or rotor diameter. The rotor diameter with controller parameters was optimized in a co-design optimization study performed in [9], with the objective of reducing the cost of energy under tower loads and blade strain constraints. Their purpose was the development of novel designs for the future generation of turbines designed for mature markets with a power capacity of 5 MW and a rotor diameter of 206 m. Results indicated an increase in rotor diameter to 220 m, reducing the cost of energy by 1.3% without affecting loads at the tower base. This study provided an optimized rotor design with any relation to the RDN and no wind potential consideration, which was based on a WT baseline design. The tower hub height and nominal power were not studied with respect to rotor diameter in the design variables. A new optimization method was developed in [10] and applied for a small-scale WT of 1 kW blade aerodynamic geometry design optimization as a function of the optimal chord length and twist angle distributions. The power coefficient was the studied objective function, and the rotor diameter, tip-speed ratio, and nominal wind speed were the design variables. The lift and drag aerodynamic coefficients were determined experimentally. The obtained new WT design results were more significant than those of the tested turbine, reaching a higher power output at a lower wind speed value. In this study, the aerodynamic geometry of a small-scale WT was optimized to enhance its power output; however, no economic evaluation of the design and grid connection constraint evaluation were performed. In addition, the design provided is based on reference WT data not suggested based on the available wind potential at a selected site and the connected RDN constraints, which constitute the interest of our work. Reference [11] proposed an optimization criterion method for the optimal design of a steel conical turbine tower considering different structural reliabilities and uncertainties. The design variables examined in this study were tower thickness and bolt type. Furthermore, this method was proposed for offshore applications. In contrast to this study, different WT design variables were studied in this work for onshore applications. In [12], the optimization of a wind farm was performed by varying the tower hub height to maximize the generated energy and reduce its cost. The hub heights of the upper and lower bounds considered in the optimization were 165 m and 65m, respectively. Reference [13] determined the optimized tower hub height distributions of two onshore wind farms by studying different optimization scenarios that consider the power output of the wind farm and cost variations. The optimization was performed using Monte Carlo simulations. In both previous studies, only the WT tower hub height design parameter was studied in the optimization of wind farms, and there was no evaluation of the rotor diameter and nominal power. In addition, the connected grid characteristics of the studied wind farm were not included in the optimization. These design parameters and RDN constraints were considered in this study.

Optimal Wind Energy integration in the distribution Network was much studied in the literature. Reference [14] involved an economic dispatch model of an active distribution network considering the spatial-temporal correlation of wind power output, where the active and reactive power optimal dispatches were optimized simultaneously. The proposed model proved the stability of the system voltage level, system loss, and operational cost reduction and enhanced the system operation efficiency. Reference [15] presented a stochastic optimal power flow to obtain the best scheduled power from wind farms integrated into the power system, while reducing the total operational costs using a novel metaheuristic method called the Aquila Optimizer. The Weibull probability distribution function was used to describe the wind speed. In these studies, optimal WT design optimization was not studied for WTs integrated into the power system.

In addition to the optimal power flow in a power system while integrating wind energy, there are researchers who are interested in the optimal size and location of WTs in the Radial Distribution Network (RDN). Reference [2] performed a study on the power system voltage stability and power loss reduction, evaluating different penetration levels of WT active power and different power factors. Load flow calculation was carried out using the forward-backward sweep method, and the optimal location and size of the WT were obtained using the Grid Search Algorithm. The voltages along the tested radial system were restricted to 1 ± 0.05 pu. In [3], the Salp Swarm Algorithm was applied for the optimal allocation of WT-based distributed generation units in the distribution system, minimizing the total power and energy losses, and improving the distribution system voltage. They integrated three WTs in a 69 bus tested system for an energy loss reduction of 66%. Reference [16] developed an optimization model for the optimal placement and sizing of WTs, considering their reactive power capacity, wind speed, and demand curves, with objective power losses in AC distribution network minimization. Furthermore, to address the uncertainties in wind power generation, an ANN was used for short-term forecasting. The maximum number of WTs installed in the tested systems was restricted from zero to three. In these studies, the optimal location and size for WT installation in the distribution system corresponded to the bus node that had the minimum power loss value. In addition, there was no evaluation of the economic benefits of WT installation in the RDN.

Economic analysis of the optimal WT size and location in the RDN has been performed by some researchers. Reference [17] involved a multi-objective optimization method for distribution network operators using a multi-objective genetic algorithm and market-based optimal power flow to determine the optimal number, size, and placement of WTs among different WTs selected and candidate buses. The main optimized objective functions were the total energy loss minimization and NPV associated with the WT investment over the planning horizon maximization. A decision framework for the optimal planning of wind power plants with technology selection in a distribution network for various bus locations was proposed in [1]. NPV was also the objective function to be maximized. In these studies, the optimal WT size was selected among evaluated technologies from the market, and the best bus locations for WTs installation were based on the wind profile. A not commercialized WT design is proposed in this study and the best bus location is selected from an economic analysis.

Based on all the cited studies, we can conclude that the optimal WT size and location in the RDN were given for power loss reduction, NPV maximization, or both. The optimal design for the WT is often based on commercialized technologies selected from the market or based on bus location with minimum power loss value. No study has provided an adequate WT design based simultaneously on the wind profile of the evaluated site and the RDN characteristics to evaluate the economic benefits of the proposed design. This constitutes the interest of this study and its originality is contained in a no existing design in the market proposition. We propose not commercialized WT technical parameters, such as D_g, H_g, and nominal power, which are not selected from the available WT technology datasheets in the market, such as the performed studies mentioned before, where the optimal design proposed among the evaluated ones was that which presented the minimum cost of energy, low power loss reduction, or maximum NPV. However, in this study, these three technical parameters are determined through an economic optimization problem resolution, which constitutes the novelty of this work.

The present paper is a continuation of our previous study carried out in [18]. An economic decision making model is presented to optimal design the future WTs based on: the available wind potential of the studied site described by the Weibull probability density function, the RDN electrical characteristics, and some other input parameters needed for the optimization problem evaluation including: the Wind speed operating range parameter χ, the nominal Wind speed of WT $v_{\mathrm{n,g}}$, and the Rotor rotation speed $N_{rpm,g}$. χ is selected from [19], $v_{n,g}$ and $N_{rpm,g}$ are estimated to be an average values from a study performed already in [18] of 23 existing WTs in the market and that are most installed in onshore applications. An economic optimization problem is studied, where the NPV of the net incomes from wind energy generation maximization is the optimized objective function. Considering grid constraints, including voltage stability and reliability of the power system related to the optimal power flow in the RDN, the decision-making model provides the optimal size of the WT technology (D_g, H_g, and nominal power) for different bus nodes of the RDN. The adequate placements among all bus nodes for the installation of the WT are those that present the maximum NPV value.

The contributions of this paper are as follows:

- An economic decision-making model based on a constrained optimization problem for the optimal design of future WTs connected to an RDN is proposed. This model is built by first modeling the annual energy generated by the WT, then constructing the optimization problem elements: design variables, constraints, and the objective function. The objective function in the optimization problem is the maximization of the NPV of wind energy incomes considering: the available wind potential and the WT geometrical design variables D_g and H_g, and subject to the electrical RDN constraints to maintain power system stability.
- In addition, to deal with the intermittent characteristic of wind energy related to the variability of wind speed, an ANN was used to predict the wind speed distribution in Essaouira City compared to the observed data for a time horizon of one year. This prediction conducts to a good estimation of the generated energy by the WT, which improve also the effectiveness of our proposed decision making model in determining the future design of WTs
- Using any optimization algorithm from existing algorithms, the developed optimization problem can be resolved. Technical WT parameters, including D_g, H_g, and nominal power, were determined for the different bus nodes in the RDN. The resulting WT design constitutes the best trade-off for the economic NPV indicator.
- The effectiveness of the proposed decision-making model was validated using the electrical parameters of the IEEE 9 and IEEE 33 Bus RDN test systems. A specific WT technology design is proposed for each evaluated bus node of both the evaluated RDN systems.

The proposed economic decision-making model acts as a support for decision makers to optimally size the WTs as a function of wind potential at their site of interest and the connected RDN characteristics to avoid power system instability problems. Furthermore, it constitutes an inspiration for other research projects in WT design optimization to come out at the end with an applicable model in the industry. The remainder of this paper is structured as follows. The economic decision-making model problem formulation is presented in Section II, the obtained results are presented and discussed in Section III, and a final conclusion is given in Section IV.

II. PROBLEM FORMULATION

A. WIND SPEED FORCASTING

The intermittent characteristic of wind energy generated from WTs is related to the variability of the wind speed. In addition, the wind power captured by the rotor of the WT is a function of the cubic wind speed. Therefore, a few wind speed variation has a significant impact on the generated energy estimation. Thus, the greater the effectiveness of wind speed prediction, the greater the estimated generated energy is real. The ANN is the method utilized in this study for hourly wind speed forecasting, minimizing the error compared to previously measured data. This method is a subset of Artificial Intelligence that is widely used for prediction and has proven its effectiveness in providing good prediction results [20]. The ANN can effectively predict future stochastic variables, such as wind speed, by imitating the human neural biological network, which saves the entered data in its memory. ANN tends to reduce the error between the entered and predicted data [16].

There are two ways of making a machine learn automatically using ANN: supervised and unsupervised techniques [20]. In supervised learning, there are inputs and awaited output data; however, there is no specific data structure for unsupervised learning. In this study, supervised learning was adopted to forecast the hourly wind speed in Essaouira City for a time horizon of one year using a feed-forward neural network model trained with the Levenberg-Marquardt back-propagation algorithm. Hence, the ANN structure consists of three main components: an input layer linked to the sources of information, a hidden layer composed of several neurons, and an output layer containing the information sent from the ANN [21]. Note that an ANN model could contain several hidden layers with different numbers of neurons in each of layer.

In the feed-forward neural network every input 'x' is combined with a weight 'w' and their sum is added to a parameter called bias 'b' to generate a single value 'z' for a nonlinear mathematical function '$f(z)$' called 'Sigmoid' contained in the bottom of each neuron in the hidden layer [16], [21]. This function is used as a nonlinear activation function in the hidden layer, and another linear fitting function called 'fitnet' is used in the output layer to fit the neural network output. z and $f(z)$ are given as follows [21], [22].

$$z = \sum wx + b \tag{1}$$

$$f(z) = \frac{1}{1 + e^{-z}} \tag{2}$$

Weights and bias are the main parameters in the ANN model calculated at the training time and changed at the testing time to reduce the error between the predicted and measured data. Synchronization of the previous parameters was performed using the back-propagation algorithm [21]. The regression coefficient 'R' and Mean Square Error 'MSE' are the error indicators used in this study to evaluate the performance of the ANN involved in forecasting wind speed at the location cited. An R value close to one and an MSE near zero leads to good forecasting results. The R and MSE equations are given by [21]:

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left(v_{mes,i} - v_{pred,i}\right)^2 \tag{3}$$

$$R = \frac{\sum_{i=1}^{N} \left(v_{mes,i} - \overline{v_{mes,\iota}}\right)\left(v_{pred,i} - \overline{v_{pred,\iota}}\right)}{\sqrt{\sum_{i=1}^{N} \left(v_{mes,i} - \overline{v_{mes,\iota}}\right)}\sqrt{\sum_{i=1}^{N} \left(v_{pred,i} - \overline{v_{pred,\iota}}\right)}} \tag{4}$$

where, N is the number of samples, $v_{mes,i}$ is the measured wind speed, $v_{pred,i}$ is the predicted wind speed, and ($\overline{v_{mes,i}}$, and $\overline{v_{pred,i}}$) are the actual mean value.

B. WEIBULL DISTRIBUTION

The Weibull distribution was used in this study as it provides a good description of the wind speed distribution [18]. It is associated with a probability density function f_i^l, characterized by two mean parameters, k^l and C^l(m/s), named shape and scale parameters, respectively, of location l.

$$f_i^l = \left(\frac{k^l}{C^l}\right)\left(\frac{v_i}{C^l}\right)^{k-1} exp\left(-\frac{v_i}{C^l}\right)^k \tag{5}$$

The k^l and C^l parameters can be estimated using several empirical methods such as the Lysen, standard deviation, and Moroccan methods [23], [24]. In addition, R and MSE error indicators were used in this case to select the most accurate method that determines the Weibull parameters that correctly fit the measured wind speed distribution in Essaouira. The standard deviation was the selected method in this study, giving the best Weibull parameters ($k^l = 2.56$, $C^l = 8.63$ m/s) that correctly describes the available measured wind speed distribution measured at initial height $H_0 = 50$ m of the year 2015 in Essaouira [25], with R and MSE values equal to 1 and 0.1, respectively. This method is also used to determine the new Weibull parameters for the achieved ANN predicted wind speed data. The Weibull parameters calculated using the measured and predicted data are having the same height measurement $H_0 = 50$ m. Standard deviation formulas for k^l and C^l determination are given by the following [23], [24]:

$$k^l = \left(\frac{\sigma}{v_{average}}\right)^{-1.086} \tag{6}$$

$$C^l = \frac{v_{average}}{\Gamma\left(1 + \frac{1}{k^l}\right)} \tag{7}$$

$$v_{average} = \frac{1}{N}\sum_{i=1}^{N} v_i \quad (8)$$

$$\sigma\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(v_i - v_{average}\right)^2} \quad (9)$$

where, Γ is the gamma function, $v_{average}$ and σ are the mean and standard deviation of wind speed respectively, and N is the number of wind speed samples.

The Weibull probability density function f_i^l describing the wind speeds is modified automatically with the estimated WT tower heights H_g given by the present economic decision-making model to $f_{i,,h}^l$ by extrapolating the Weibull parameters k^l and C^l calculated using the ANN predicted wind speed data at $H_0 = 50$ m using the modified Mikhail formulas given in [26] and [27] in order to follow the impact of WT tower height H_g variation occurred during the resolution of the optimization problem on: the Wind speed distribution, the generated energy by the WT, and whole WT design optimization problem presented in subsection D. The adopted formulas for extrapolation are given by the following [26], [27]:

$$C_{H_g}^l = C_{H_0}^l (\frac{H_g}{H_0})^p \quad (10)$$

$$p = \alpha_0 \left[\frac{1-\frac{\ln(C_{H_0}^l)}{\ln(67)}}{1-\frac{\alpha_0 \ln\left(\frac{H_0}{h_r}\right)}{\ln(67)}}\right] \quad (11)$$

$$k_{Hg}^l = k_{H0}^l \left[\frac{1-\frac{\alpha_0 \ln\left(\frac{H_0}{h_r}\right)}{\ln(67)}}{1-\frac{\alpha_0 \ln\left(\frac{H_g}{h_r}\right)}{\ln(67)}}\right] \quad (12)$$

$$\alpha_0 = (\frac{z_0}{h_r})^{0.2} \quad (13)$$

where, p is the power law exponent, h_r is the reference height equal to 10 m given by [27], α_0 is the surface roughness exponent and z_0 is the surface roughness length of site, H_g is the estimated height by the present decision support model, H_0 is the initial height of measured wind speeds $H_0 = 50$ m, $C_{H_g}^l$ and k_{Hg}^l are the extrapolated Weibull parameters at the new height H_g, and, $C_{H_0}^l$ and $k_{H_0}^l$ are the Weibull parameters calculated using the ANN predicted wind speed data at H_0.

The Weibull distribution function $f_{i,,h}^l$ is included in our decision-making model proposed for WT design and location problems, as discussed in the above paragraph and presented in the following subsection.

C. WIND ENERGY GENERATION MODELING

The WT model is composed of three main components: rotor, gearbox, and generator [1]. The yearly generated energy $E_{t,g}^l$ from WTs design technologies 'g' proposed by the present decision making model for the bus nodes location 'l' (l=1.….M) in the RDN is modeled using the following formula [18]:

$$E_{t,g}^l = \frac{1}{2}\left[8760\left(\rho S_g \sum_{i=1}^{N} f_{i,h}^l C_{p,i,g} v_i^3\right)\right] \quad (14)$$

where, ρ (kg/m3) is the air density, S_g(m^2) is the rotor swept surface, $f_{i,h}^l$ is the discretized Weibull function with tower height H_g at the studied site, $C_{p,i,g}$ is the total efficiency of the WT, and v_i(m/s) is the wind speed of the ith class.

$$S_g = \frac{\pi D_g^2}{4} \quad (15)$$

$$C_{p,i,g} = \eta_{gear,i,g} \quad C_{pr,i,g} \quad \eta_{gen,i,g} \quad (16)$$

where, Dg is the WT Rotor diameter (m), $\eta_{gear,i,g}$ is the WT gearbox efficiency, $C_{pr,i,g}$ is the WT Rotor power coefficient, and $\eta_{gen,i,g}$ is the WT generator efficiency.

The WT Rotor power coefficient is computed as follows [18], (17)–(21), as shown at the bottom of the page, where, $C_{pr,g}^{max}$ is the Rotor maximum power coefficient, $v_{p,g}$ the optimal WT operation wind speed, χ is the Wind speed operating range parameter, $v_{n,g}$ is the nominal Wind speed of WT, $\lambda_{max,g}$ is the maximum speed rate, BN$_g$ is the number of WT blades, cd/cl is the ratio between drag and lift coefficients, ω_g is the angular rotation speed of the Rotor, $N_{rpm,g}$ is the Rotor rotation speed (rpm).

$$C_{pr,i,g} = C_{pr,g}^{max}\left(exp\left[-\frac{(ln\, v_i - ln\, v_{p,g})^2}{2(ln\,\chi)^2}\right]\right) \quad (17)$$

$$v_{p,g} = \frac{v_{n,g}}{exp\left[3(ln\,\chi)^2\right]} \quad (18)$$

$$C_{pr,g}^{max} = 0.593\left[\frac{\lambda_{max,g}(BN_g)^{0.67}}{1.48+\left((BN_g)^{0.67}-0.04\right)\lambda_{max,g}+0.0025(\lambda_{max,g})^2}\right] - 0.593\left[\frac{1.92(\lambda_{max,g})^2 BN_g}{1+2\lambda_{max,g}BN_g}.\frac{C_d}{C_l}\right] \quad (19)$$

$$\lambda_{max,g} = \frac{D_g\omega_g}{2v_{p,g}} \quad (20)$$

$$\omega_g = \frac{2\pi N_{rpm,g}}{60} \quad (21)$$

The WT gearbox efficiency is computed as follows [18]:

$$\boldsymbol{\eta_{gear,i,g}} = \mathbf{1} - \left[\left(\mathbf{1} - \boldsymbol{\phi_{gear,g}} \right) \left(\frac{\boldsymbol{P_{n,g}}}{\mathbf{4}\boldsymbol{P_{r,i,g}}} + \frac{\mathbf{3}}{\mathbf{4}} \right) \right] \tag{22}$$

$$\boldsymbol{\phi_{gear,g}} = \mathbf{0.89} (\boldsymbol{P_{n,g}})^{\mathbf{0.012}} \tag{23}$$

$$\boldsymbol{P_{n,g}} = \boldsymbol{P_{p,g}.exp}(\mathbf{4.5}(ln\ \chi)^{\mathbf{2}}) \tag{24}$$

$$\boldsymbol{P_{p,g}} = \frac{\mathbf{1}}{\mathbf{2}} \boldsymbol{\rho C_{pr,g}^{max} S_g (v_{p,g})^{3}} \tag{25}$$

$$\boldsymbol{P_{r,i,g}} = \frac{\mathbf{1}}{\mathbf{2}} \boldsymbol{\rho C_{pr,i,g} S_g v_i^3} \tag{26}$$

where, $\phi_{gear,g}$ is the gearbox efficiency factor, $P_{n,g}$ is the WT nominal power, $P_{p,g}$ is the optimal power corresponding to optimal wind speed $v_{p,g}$, and $P_{ri,g}$ is the WT Rotor power captured. As discussed in subsection A $P_{ri,g}$ is a function of cubic wind speed.

The WT generator efficiency is computed as follows [18]:

$$\boldsymbol{\eta_{gen,i,g}} = \mathbf{1} - \left[\left(\mathbf{1} - \boldsymbol{\phi_{gen,g}} \right) \left(\mathbf{5} \left(\frac{\boldsymbol{P_{gear,i,g}}}{\boldsymbol{P_{n,gen,g}}} \right)^{\mathbf{2}} + \mathbf{1} \right) \times \left(\frac{\boldsymbol{P_{n,gen,g}}}{\mathbf{6}\boldsymbol{P_{gear,i,g}}} \right) \right] \tag{27}$$

$$\boldsymbol{\phi_{gen,g}} = \mathbf{0.87} (\boldsymbol{P_{n,g}})^{\mathbf{0.014}} \tag{28}$$

$$\boldsymbol{P_{gear,i,g}} = \boldsymbol{\eta_{gear,i,g} P_{r,i,g}} \tag{29}$$

$$\boldsymbol{P_{n,gen,g}} = \boldsymbol{\phi_{gen,g} \phi_{gear,g} F_{s,g} P_{n,g}} \tag{30}$$

where, $\phi_{gen,g}$ is the generator efficiency factor, $P_{gear,i,g}$ is the gearbox generated power, $P_{n,gen,g}$ is the WT generator nominal power, and $F_{s,g}$ is the factor of service of the gearbox which take different values related to the WT regulation type (1.75, 1.25, and 2 for pitch-constant-speed, pitch-variable-speed, and stall-constant-speed regulations respectively).

Discounting the losses 'α' that occur during the WT energy generation, the real yearly generated energy $E^l_{t,g,real}$ from WTs became:

$$\boldsymbol{E^l_{t,g,real}} = \boldsymbol{E^l_{t,g}} - \boldsymbol{\alpha E^l_{t,g}} \tag{31}$$

D. OPTIMIZATION PROBLEM MODELING

An economic optimization problem is studied in this study to obtain the optimal WT design parameters: D_g, H_g, and nominal power function, the wind profile of the studied site, and under the RDN constraints. Discretized Weibull parameters that describe the forecasted wind speed potential using the ANN model were used in this optimization. The main objective of this constrained optimization problem is to maximize the economic benefits of WT-generated energy using the *NPV* indicator. NPV is a sophisticated economic indicator used to evaluate the profitability of an investment associated with a given project, considering all future cash flows in and out of the project at a given discount rate [18]. The higher the NPV value, the higher the profitability of the investment, supporting investors to invest in the wind energy field.

The optimization problem resolution permits the selection of candidate bus node locations for WT installation in the tested RDN system based on the registered NPV. The optimization problem consists of three main components: objective function, design variables, and constraints, defined below.

1) OBJECTIVE FUNCTION

The objective function is the element to be optimized. In this study, the *NPV* maximization of the wind energy generation incomes is the objective function used. The adopted *NPV* model is given by the following formula [18]:

$$NPV^l_g = \sum_{t=1}^{n} \frac{C^{Net,l}_{benif,t,g}}{(1+r)^t} - I^l_{t=0,g} \tag{32}$$

$$C^{Net,l}_{benif,t,g} = C^l_{benif,t,g} - C^l_{OM,t} - T^l_{t,g} - D^l_{t,g} \tag{33}$$

where, $I^l_{t,g}$ is the WT Investment made in year t (\$), $C^l_{benif,t,g}$ is the total benefits, $C^l_{OM,t}$ is the WT Operation and Maintenance cost in year t (\$), $D^l_{t,g}$ is the annual depreciation expense (\$), $T^l_{t,g}$, is Tax levy (\$), n is the WT lifetime, r is the Discount rate, and $C^{Net,l}_{benif,t,g}$ are the total net Wind energy generation benefices removing all the expenses related to tax payment, the costs of operation and maintenance of WT, and the recovered investment ($D^l_{t,g}$).

The depreciation expense $D^l_{t,g}$, estimates the value of the investment at the end of the WT lifetime. Given as follows [18]:

$$D^l_{t,g} = \frac{I^l_{t,g}}{n} \tag{34}$$

Tax levy $T^l_{t,g}$, is the tax payment associated with registered wind energy economic revenues. Value Added Tax is the tax system applied in this study, corresponding to the country of the evaluated site [18].

The total net wind energy generation benefits $C^{Net,l}_{benif,t,g}$ per year t are measured using two different income parameters [1], [18]: $C^{benif,l}_{Sal,t,g}$ and $C^{benif,l}_{Inc,t,g}$, which are the incomes from electrical energy sales and incentives for green energy production, respectively. Defined as follows:

$$C^l_{benif,t,g} = C^{benif,l}_{Sal,t,g} + C^{benif,l}_{Inc,t,g} \tag{35}$$

$$C^{benif,l}_{Sal,t,g} = C_S E^l_{t,g,real} \tag{36}$$

$$C^{benif,l}_{Inc,t,g} = C_{In} E^l_{t,g,real} \tag{37}$$

where, C_S is the purchase tariff of electricity, and C_{In} are Sales cost due to incentives for green energy production.

The operation and maintenance cost of the WT is estimated as follows [18]:

$$C^l_{OM,t} = \eta I^l_{t,g} + \xi C^{benif,l}_{Sal,t,g} \tag{38}$$

where, η and ξ are investment and incomes factors, respectively.

For every optimized WT design 'g' at the bus location, 'l', the WT technology investment cost model is composed of

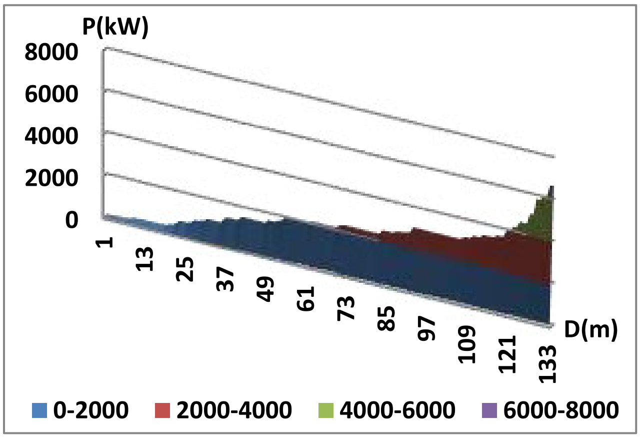


FIGURE 1. WT power variation function rotor diameter.

several costs, whose details are given in the authors previous work [18]:

$$I_{t,g}^{l}=C_{T,g}^{l}+C_{AI,g}^{l}+C_{EI,g}^{l}+C_{EP,g}^{l}+C_{RCW,g}^{l}+C_{F,g}^{l}+C_{WT,g}^{l} \tag{39}$$

where, the associated investment costs are: $C_{T,g}^{l}$ is the WT Transportation cost, $C_{AI,g}^{l}$ is the WT Assembly and Installation cost, $C_{EI,g}^{l}$ is the Electrical Interface cost, $C_{EP,g}^{l}$ is the Engineering and Permits cost, $C_{RCW,g}^{l}$ is the Roads and Civil Work cost, $C_{F,g}^{l}$ is the Fondation cost, and $C_{WT,g}^{l}$ is the WT cost.

Note that the adopted WT cost model $C_{WT,g}^{l}$ is the result of the authors' previous study [18].

2) DESIGN VARIABLES AND CONSTRAINTS

Design Variables are the input elements of the optimization problem, which sometimes constitute a form of constraint when they are varied between the maximum and minimum values to obtain the optimal solution feasible at these limits [18]. Two types of constraints were employed in this study. The first type is related to the geometrical design variables of WT (D_g and H_g) normally used in onshore installations, where we studied the available technologies in the market regarding their power capacities and their corresponding diameters, where the WTs capacity studied was between 50 kW and 6000 kW [28]. Fig. 1 shows the obtained variation area of the WTs power with the possible diameters.

Hence, we resulted in the following WT design constraints with a specific variation for the rotor diameter D_g, and the possible associated tower height, H_g, is estimated using equation (41) [18]:

$$40\,m \le D_g \le 200\,m \tag{40}$$

$$\frac{D_g}{2}+15 \le H_g \tag{41}$$

The second type is the RDN electrical constraint modeled through the power flow equation (42) used in our decision-making model to optimally design the WTs connected to the RDN. The active power flow generated by the WT is controlled while feeding the load [17], [29].

$$P_{WT,g}^{l}-P_{Load}^{l}-P_{Loss}^{l}=0 \tag{42}$$

$$\text{With: } P_{WT,g}^{l}=P_{n,g} \tag{43}$$

$$P_{Loss}^{l}=V_l\sum\nolimits_{j=1}^{M}V_j\left[G_{lj}\cos\left(\delta_l-\delta_j\right)+B_{lj}\sin\left(\delta_l-\delta_j\right)\right] \tag{44}$$

where, $P_{WT,g}^{l}$ is the WT generated active power, P_{Load}^{l} is the load active power, P_{Loss}^{l} is the power loss in the branch lines of the RDN, V_l and V_j are the voltage magnitudes at buses l and j respectively, G_{lj} and B_{lj} are the real and imaginary parts of the admittance matrix respectively of the jth row and lth column, respectively, δ_l and δ_j are the voltage angles at buses l and j, respectively, M is the number of buses.

In addition, the voltage magnitude in the RDN constraint is employed as the RDN design variable, which varies within 5% of the initial value in all bus nodes.

$$V_l/V_j(p.u)=1\pm 0.05 \tag{45}$$

As mentioned in the first section, this study is a continuation of our previous work [18]. The adopted decision-making model presented in this section is described in general by the NPV model, which includes all the WT models cited previously, and was already verified and validated in our previous work [18] with an existing model in the literature [1]. Compatibility was found between the two models, demonstrating the effectiveness of the model adopted in this study. In addition, the optimization problem studied in [18]was used in this study with new constraints, specifically the RDN constraints presented before. This constrained optimization problem was also verified and resolved in [18] using three different algorithms: genetic, fmincon, and PSO, to ensure the efficiency of the results obtained. The optimized objective function (NPV) yielded nearly the same results; hence, the optimization problem could be resolved using one of these optimization algorithms. Further details are provided in [18]. The wind site characteristics described by the Weibull distribution parameters (k^l and C^l) and the WT design variables (D_g and H_g), in addition to the RDN design variables (V_l and V_j), are specified for the NPV objective function model. The NPV of the WT energy incomes is evaluated under all the restrictions mentioned before in the optimization problem using the optimization algorithm to determine the optimal WT design output that maximizes the objective function. The genetic algorithm was used to solve the optimization problem in the following steps:

- Starting creating a random initial population containing several individuals.
- Objective function evaluation at each individual of the population created.
- Create a new population based on the individual selection of the current population with the maximum objective function value (NPV). The selected individuals

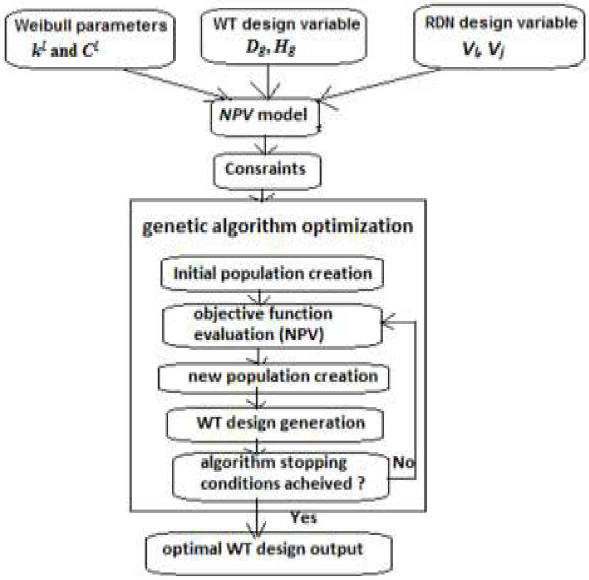


FIGURE 2. Optimization process flowchart.

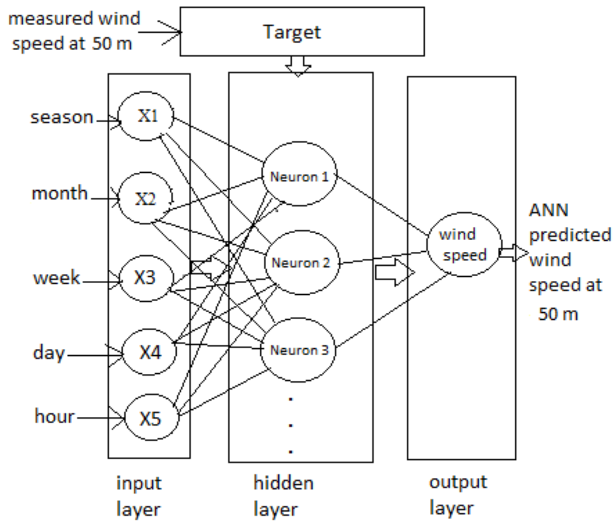


FIGURE 3. Simplified ANN model architecture.

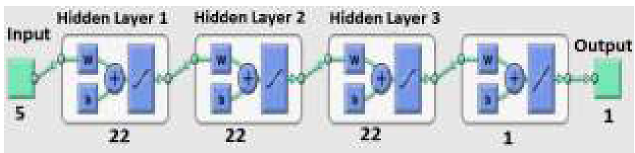


FIGURE 4. Resulted ANN model structure.

are called parents and are used by crossover or mutation operators of the ga algorithm to produce children. Mutation involves making random changes to a single parent; however, the crossover operator combines the vector entries of a pair of parents. A new population was formed with the creation of children.
- WT design parameters is generated from the new population created

These steps are repeated to generate the best new population that gives the most feasible WT design solution until reaching one stopping criteria of the algorithm such as maximum number of iterations or time limit. The global optimization process is shown in Fig.2.

III. RESULTS AND DISCUSSION

As mentioned before, the objective of this paper is to present a decision making model that gives the optimal WT design including three main technical parameters studied in this work ($\boldsymbol{D_g}$, $\boldsymbol{H_g}$, and the nominal power) based on wind profile of the studied site and under the RDN electrical characteristics; in addition to select the most candidate buses for WT installation from the evaluated RDN system. Thus, the proposed decision-making model presented previously is validated in determining the optimal WT design function wind potential and the previously mentioned constraints using two different RDN test system data: IEEE 9 and IEEE 33 bus test systems [2], [30]. The results are then presented and discussed in this section.

As discussed previously, the ANN was used to validate the wind site profile. The hourly measured wind speed data in Essaouira Moroccan city in 2015 at initial height $H_0 = 50$ m was used as the target to reach in the ANN model to test the studied RDN systems [25]. The global measured wind speed data consisted of 8760 values. Part of this data is used for training the ANN, and the rest is used to test the efficiency of the results involved before the ANN model performs the prediction. Calendar data, including season, month, week, day, and hour, were used as inputs, and the anticipated output was the wind speed. The simplified ANN architecture used in this study is illustrated in Fig. 3. The best prediction results were obtained with an ANN structure composed of three hidden layers and 22 neurons in each hidden layer, as shown in Fig. 4. In addition to a data partition in the learning phase of 80% in the training and 20% in the testing where the minimum errors were reached, with R and MSE values of 0.97 and 0.57, respectively, as shown in Fig. 5 and 6.

The hourly wind speed data measured and predicted by the ANN model for the year 2015 in Essaouira City is composed of 8760 wind speed values, as presented in Fig.7. These forecasted wind speed values were used to find the new Weibull function parameters k^l and C^l, using the equations discussed and presented in subsection B. This Weibull function is required for the WT energy generation estimation, which has a direct impact on the objective function of the WT design optimization problem, as presented previously in Subsections C and D.

Achieved results conduct nearly to the same measured Weibull parameters values with a $k^l = 2.62$, $C^l = 8.63$ m/s, and $v_{average} = 7.17$ m/s, as presented in Table 1. This demonstrates the stability of the future wind potential at the studied

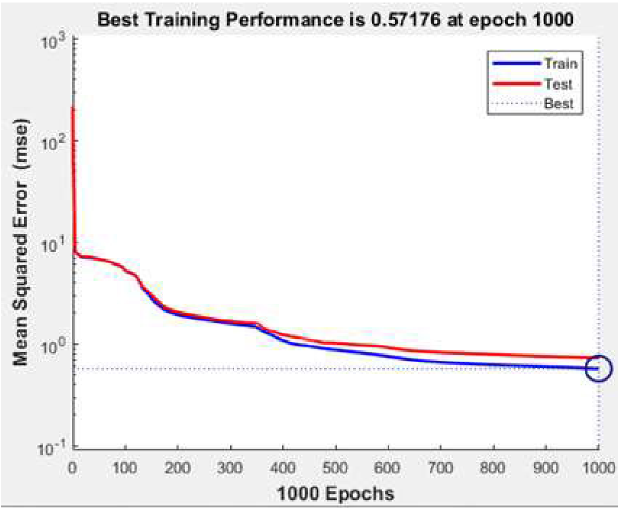


FIGURE 5. MSE error results of the ANN model.

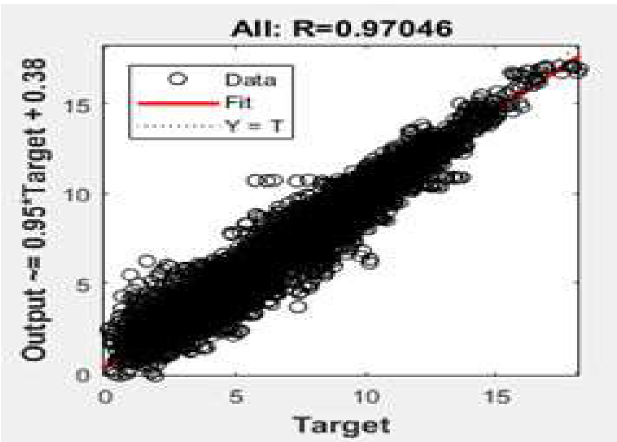


FIGURE 6. Regression coefficient R error results of the ANN model.

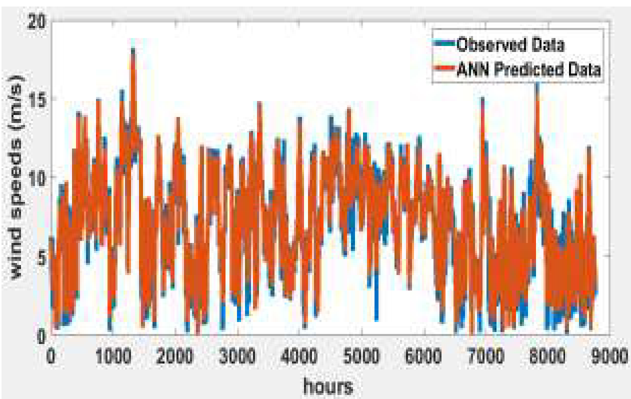


FIGURE 7. Essaouira observed and predicted wind speeds.

site, leading to a real estimation of the generated wind energy. This supports the validity of WT designs proposed by our decision-making model in the future.

TABLE 1. Essaouira weibull parameters atH_0 = *50 m.*

	k^l	C^l (m/s)	$v_{average}$(m/s)
With measured wind speeds data	2.56	8.63	7.17
with ANN Predicted wind speeds	2.62	8.63	7.17

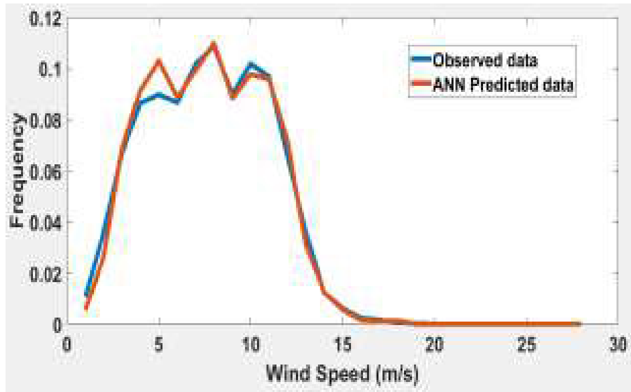


FIGURE 8. Observed and predicted Weibull data in Essaouira city.

Using these predicted and measured Weibull parameters, and by classifying the associated wind speed data into different classes varying between 1 m/s and 29 m/s, the Weibull probability density function presenting the wind speed frequency was calculated and fitted to the measured and predicted Weibull parameters. The results are shown in Fig. 8. This figure shows the observation probability of wind speeds and demonstrates more the stability of wind potential in Essaouira City, where the observed and predicted Weibull function data results are nearly the same, with small differences at 5 m/s and 10 m/s, but generally, the average wind speed is identical ($v_{average}$ = 7.17 m/s).

As discussed and presented in subsection A and C, a few wind speed difference has an important impact on the generated wind energy. Hence, the Weibull parameters obtained using the ANN predicted wind speed data are used in the rest of the calculation in this study and extrapolated automatically with tower height H_g values obtained by the present economic decision-making model using the extrapolation method discussed in subsection B, to overcome its influence on the wind speed profile.

The input parameters used in the optimization problem study include the Weibull distribution parameters obtained previously through the forcasted wind speed values by the ANN model (k^l = 2.62 and C^l = 8.63 m/s), in addition to other input parameters selected from our previous study performed in [18] needed in this evaluation mainly: the WT nominal wind speed $v_{n,g}$ = 13.2 m/s, wind speed operating range χ = 1.7, rotor rotation speed $N_{rpm,g}$ = 18.15 rpm, drag and left ratio C_d/C_l = 1/120,, air density ρ = 1.225, WT energy generation losses percentage α = 5%, tax

TABLE 2. Optimal WT designs parameters for the IEEE 9 bus radial distribution system.

Buses	$P^{l}_{WT,g}$ (kW)	D_g (m)	H_g (m)
1	5128.75	200	115
2	5128.75	200	115
3	2654.17	135.39	82.70
4	2613.72	134.23	82.11
5	2140.58	120.08	75.04
6	1494.87	98.79	64.39
7	1575.97	101.63	65.82
8	1230.57	89.06	59.53
9	1804.29	109.35	69.68

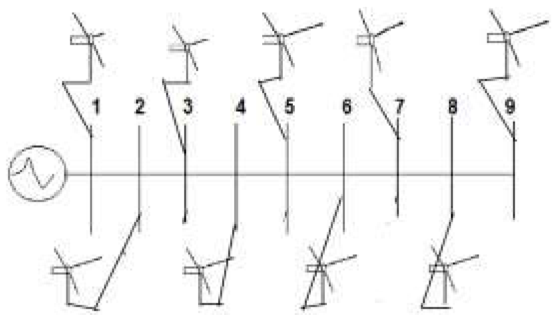


FIGURE 9. IEEE 9 Bus radial distribution network system scheme with adequate WT locations.

TABLE 3. Optimal WT designs parameters for the IEEE 33 bus radial distribution system.

Buses	$P^{l}_{WT,g}$ (kW)	D_g (m)	H_g (m)
2	1794.33	109.02	69.51
3	360.81	47.48	38.74
4	493.67	55.57	42.79
5	415.48	50.95	40.48
6	269.16	41.06	35.53
7	1049.09	81.88	55.94
8	307.62	43.86	36.93
9	221.35	37.30	33.65
10	216.16	36.87	33.43
11	783.62	70.36	50.18
12	442.63	52.60	41.30
13	172.71	33.05	31.53
14	406.24	50.38	40.19
15	318.13	44.60	37.30
16	262.14	40.53	35.26
17	179.45	33.67	31.84
18	291.06	42.68	36.34
19	1077.01	83.02	56.51
20	203.94	35.84	32.92
21	485.60	55.11	42.56
22	318.04	44.59	37.30
23	455.45	53.36	41.68
24	652.90	64.06	47.03
25	552.64	58.84	44.42
26	749.76	68.77	49.39
27	532.89	57.77	43.88
28	187.30	34.38	32.19
29	287.10	42.39	36.19
30	428.22	51.73	40.87
31	313.53	44.28	37.14
32	693.16	66.05	48.03
33	493.75	55.58	42.79

payment $T^{l}_{t,g} = 14\%$,, WT life time n=20 years, Discount rate r=8%, annual depreciation expense $D^{l}_{t,g} = 5\%$ of the investment, percentages adopted for the operation and maintenance cost $\eta = 1\%$ and $\xi = 2\%$, the purchase tariff of electricity $C_s = 0.094$ \$/kWh, and Sales cost due to incentives for green energy production $C_{In} = 0.053$ \$/kWh.

We assumed that the tested RDNs had the same wind characteristics as the studied site (Essaouira). In addition, all buses are candidates for WT installation from the wind potential viewpoint, and we propose their WT technical characteristics, including D_g, H_g, and nominal power ($P_{n,g}$). The obtained WT design parameter results are presented in Tables 2 and 3. The optimal WT design results corresponded to the predicted Weibull parameters obtained through the ANN model, which showed the stability of the wind potential compared to the observed one in Essaouira. The most suitable bus locations for wind energy generation were those presenting good economic benefits presented in the IEEE 9 and 33 schemes [2], [31] in Fig. 9 and 10.

IEEE 9 bus test system results approved its capacity for Wind energy generation for all buses presenting good economic benefits with a minimum and maximum NPV of 3.87 M\$ and 18.62 M\$ respectively, as describes in Fig. 11. However, there are only a few candidate buses for WT installation in the IEEE 33 bus test system. The most candidate buses in the IEEE 33 test system are:2, 7, 11, 19, 24, 26,

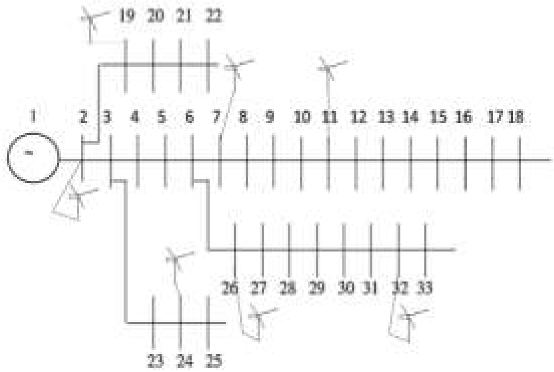


FIGURE 10. IEEE 33 Bus radial distribution network system scheme with adequate WT locations.

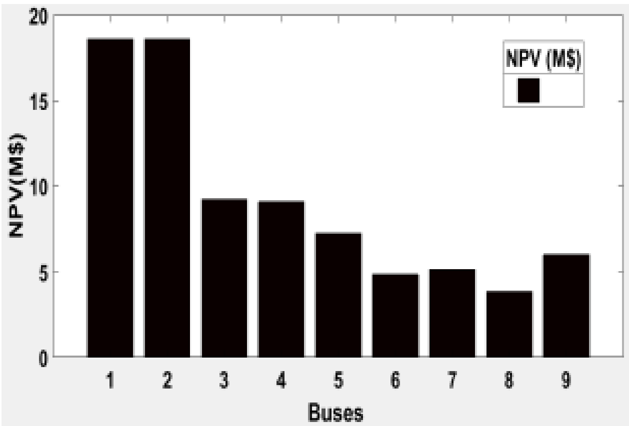


FIGURE 11. NPV results of the IEEE 9 Bus radial distribution network system in the profitable bus locations.

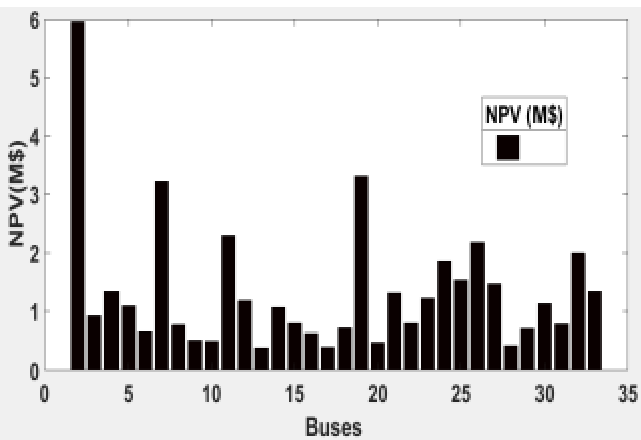


FIGURE 12. NPV results of the IEEE 33 Bus radial distribution network system in the profitable bus locations.

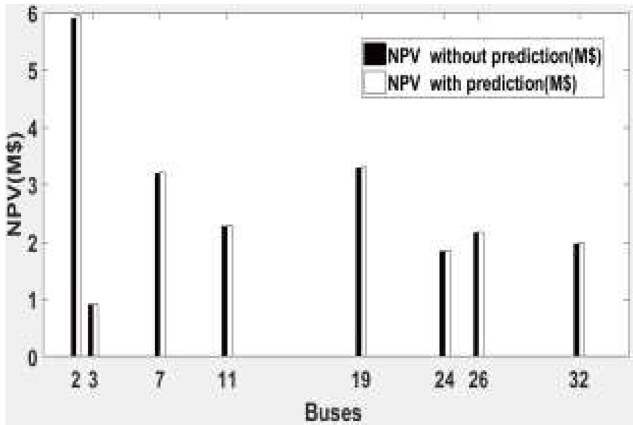


FIGURE 13. Achieved NPV results with and without ANN prediction of the IEEE 33 Bus radial distribution network system.

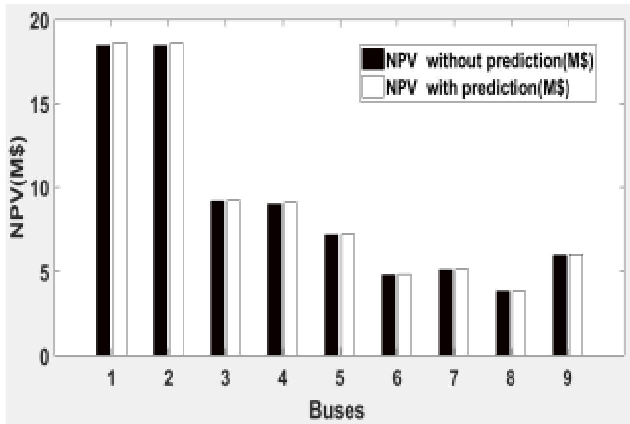


FIGURE 14. Achieved NPV results with and without ANN prediction of the IEEE 9 Bus radial distribution network system.

and 32 with an NPV of 5.95, 3.22, 2.29, 3.32, 1.85, 2.18, and 1.98 M$ respectively as described in Fig. 12.

We can remark from the IEEE 9 bus system, that we have a good wind profile at the Essaouira site, which offers the opportunity for a powerful WTs installation of more than 5 MW. However, in the case of the IEEE 33 bus system, the maximum capacity of the WT design involved with the present decision support model was approximately 1 MW. That can be explained by the grid limitations evaluated. Each RDN has its own electrical characteristics with different branch-line values. The IEEE 9 bus system is more powerful than the IEEE 33 bus system with an important active power load demand. This explains the results of this study. Therefore, the proposed WTs design follows the available wind potential and grid constraints. As discussed before, the validity of the WTs design in the future was approved by our decision-making model, using the ANN-predicted wind speed data described through the Weibull parameters. A comparison with an optimization study in the case of the initial measured Weibull parameters utilization was realized. The decision-making model involved the same WT design parameters for the both evaluated RDNs systems with nearly the same economic benefits value using the wind speed potential with and without prediction, as presented in Fig. 13 and 14. We can also observe that the use of ANN prediction results increase slightly the economic benefits of the proposed WTs design owing to its effective wind potential forecast, enhancing the generated energy, and automatically the value of NPV is enhanced in parallel. We note that these designs are not available or commercialized in the market, as suggested by this study.

IV. FUTURE WORKS AND CONCLUSION

An economic decision-making model for optimal WT design based on the wind potential of the site of interest and RDN constraints is proposed and presented as a constrained optimization problem in this paper. The technical parameters of the WT design, including the rotor diameter D_g, Tower Hub Height H_g, and WT nominal power, were determined for all the studied RDN bus nodes. In this study, we propose WTs design parameters that are not available in the market. The *NPV* of the economic benefit maximization of WT-generated energy is the objective function studied in the optimization problem. Wind speed variation has a significant effect on the WT-generated energy. Therefore, an ANN model was used to effectively forecast the wind speed potential in Essaouira City, minimizing the error compared with previously measured values. The proposed decision-making model is validated and tested using the electrical characteristics of two different RDN bus systems, namely IEEE 9 and IEEE 33 bus RDN systems. Based on the maximum value of the resulting NPV, the most candidate bus nodes for WT installation in the tested RDN systems were selected. The results obtained showed that all nine buses of the IEEE 9 system were candidates for WT installation; however, only eight candidate buses in the IEEE 33 system presented good *NPV* economic benefits. Therefore, we can conclude that the WT design depends more on the capacity of the connected RDN than on the available wind potential. In addition, the ANN model prediction results proved the stability of the future wind potential in Essaouira City, providing nearly the same Weibull distribution as the measured distribution. This supports the validity of WT designs achieved in the future. Furthermore, the adoption of the ANN-predicted Weibull parameters in the WT design optimization study slightly improved its *NPV* value compared with the measured parameters, demonstrating the impact of a few wind speed variations on the economic benefits associated with the generated wind energy. The presented decision-making model supports decision-makers in determining the optimal WT design and suitable RDN bus locations for WT installation at the site of interest. In this study, aerodynamic effects, material optimization, and power loss reduction were not considered in the evaluated optimization problem, and could be recommended for future work.

REFERENCES

[1] A. Ouammi, H. Dagdougui, and R. Sacile, "Optimal planning with technology selection for wind power plants in power distribution networks," *IEEE Syst. J.*, vol. 13, no. 3, pp. 3059–3069, Sep. 2019, doi: 10.1109/JSYST.2019.2903555.

[2] G. A. E.-A. Mahmoud and E. S. S. Oda, "Investigation of connecting wind turbine to radial distribution system on voltage stability using SI index and λ—V curves," *Smart Grid Renew. Energy*, vol. 7, no. 1, Jan. 2016, Art. no. 1, doi: 10.4236/sgre.2016.71002.

[3] A. Boliev, Kurbanov, A. Suyarov, J. Urinboy, and A. Jumanov, "Optimal integration of wind turbine based Dg units in distribution system considering uncertainties," *Int. J. Acad. Appl. Res.*, vol. 5, no. 4, pp. 183–187, Apr. 2021.

[4] H. Yang, J. Chen, and X. Pang, "Wind turbine optimization for minimum cost of energy in low wind speed areas considering blade length and hub height," *Appl. Sci.*, vol. 8, no. 7, p. 1202, Jul. 2018, doi: 10.3390/app8071202.

[5] D. Song, J. Liu, J. Yang, M. Su, Y. Wang, X. Yang, L. Huang, and Y. H. Joo, "Optimal design of wind turbines on high-altitude sites based on improved yin-yang pair optimization," *Energy*, vol. 193, Feb. 2020, Art. no. 116794, doi: 10.1016/j.energy.2019.116794.

[6] M. A. Mellal and M. Pecht, "A multi-objective design optimization framework for wind turbines under altitude consideration," *Energy Convers. Manage.*, vol. 222, Oct. 2020, Art. no. 113212, doi: 10.1016/j.enconman.2020.113212.

[7] R. Wass, "Design of wind turbine tower height and blade length: An optimization approach," Mech. Eng. Undergraduate Honors Theses, Univ. Arkansas, Fayetteville, AR, USA, 2018, p. 76.

[8] T. Ashuri, M. B. Zaaijer, J. R. R. A. Martins, and J. Zhang, "Multidisciplinary design optimization of large wind turbines—Technical, economic, and design challenges," *Energy Convers. Manage.*, vol. 123, pp. 56–70, Sep. 2016, doi: 10.1016/j.enconman.2016.06.004.

[9] N. J. Abbas, P. Bortolotti, C. Kelley, J. Paquette, L. Pao, and N. Johnson, "Aero-servo-elastic co-optimization of large wind turbine blades with distributed aerodynamic control devices," *Wind Energy*, vol. 26, no. 8, pp. 763–785, Aug. 2023, doi: 10.1002/we.2840.

[10] R. Özkan and M. S. Genç, "Aerodynamic design and optimization of a small-scale wind turbine blade using a novel artificial bee colony algorithm based on blade element momentum (ABC-BEM) theory," *Energy Convers. Manage.*, vol. 283, May 2023, Art. no. 116937, doi: 10.1016/j.enconman.2023.116937.

[11] D. Li, H. Bao, and N. Zhao, "Research of turbine tower optimization based on criterion method," *Energies*, vol. 16, no. 2, p. 906, Jan. 2023, doi: 10.3390/en16020906.

[12] A. Wolf Ciavarra, R. Valotta Rodrigues, K. Dykes, and P.-E. Réthoré, "Wind farm optimization with multiple hub heights using gradient-based methods," *J. Phys., Conf. Ser.*, vol. 2265, no. 2, May 2022, Art. no. 022012, doi: 10.1088/1742-6596/2265/2/022012.

[13] G. Kütükçü and O. Uzol, "Monte–Carlo simulations based hub height optimization using FLORIS for two interacting onshore wind farms," *J. Renew. Sustain. Energy*, vol. 14, no. 6, Nov. 2022, doi: 10.1063/5.0107244.

[14] H. Qu, F. Yang, Q. Lin, and Y. Jia, "Active and reactive power coordinated optimal dispatch in active distribution network considering spatial-temporal correlation of wind power," *IOP Conf. Ser., Earth Environ. Sci.*, vol. 687, no. 1, Mar. 2021, Art. no. 012093, doi: 10.1088/1755-1315/687/1/012093.

[15] A. K. Khamees, A. Y. Abdelaziz, M. R. Eskaros, A. El-Shahat, and M. A. Attia, "Optimal power flow solution of wind-integrated power system using novel Metaheuristic method," *Energies*, vol. 14, no. 19, p. 6117, Sep. 2021, doi: 10.3390/en14196117.

[16] W. Gil-González, O. D. Montoya, L. F. Grisales-Noreña, A.-J. Perea-Moreno, and Q. Hernandez-Escobedo, "Optimal placement and sizing of wind generators in AC grids considering reactive power capability and wind speed curves," *Sustainability*, vol. 12, no. 7, p. 2983, Apr. 2020, doi: 10.3390/su12072983.

[17] P. Siano and G. Mokryani, "Evaluating the benefits of optimal allocation of wind turbines for distribution network operators," *IEEE Syst. J.*, vol. 9, no. 2, pp. 629–638, Jun. 2015, doi: 10.1109/JSYST.2013.2279733.

[18] F.-A. Bourhim, S. Berrhazi, A. Ouammi, and R. Benchrifa, "Decision support model for optimal design of wind technologies based techno–economic approach," *IEEE Access*, vol. 9, pp. 148264–148276, 2021, doi: 10.1109/ACCESS.2021.3123561.

[19] C. T. Kiranoudis and Z. B. Maroulis, "Effective short-cut modelling of wind park efficiency," *Renew. Energy*, vol. 11, no. 4, pp. 439–457, Aug. 1997, doi: 10.1016/S0960-1481(97)00011-6.

[20] Y. P. Faniband and S. M. Shaahid, "Forecasting wind speed using artificial neural networks—A case study of a potential location of Saudi Arabia," in *Proc. E3S Web Conf.*, vol. 173, 2020, p. 1004, doi: 10.1051/e3sconf/202017301004.

[21] T. Brahimi, F. Alhebshi, H. Alnabilsi, A. Bensenouci, and M. Rahman, "Prediction of wind speed distribution using artificial neural network: The case of Saudi Arabia," *Proc. Comput. Sci.*, vol. 163, pp. 41–48, 2019, doi: 10.1016/j.procs.2019.12.084.

[22] A. Arzu, M. R. Ahmed, and M. G. M. Khan, "Wind speed forecasting using regression, time series and neural network models: A case study of Suva," in *Proc. 22nd Australas. Fluid Mech. Conf. (AFMC)*, Brisbane, QLD, Australia, Dec. 2020, p. 4, doi: 10.14264/ccee311.

[23] Y. El Khchine, M. Sriti, and N. E. El Kadri Elyamani, "Evaluation of wind energy potential and trends in Morocco," *Heliyon*, vol. 5, no. 6, Jun. 2019, Art. no. e01830, doi: 10.1016/j.heliyon.2019.e01830.

[24] M. H. Ouahabi, H. Elkhachine, F. Benabdelouahab, and A. Khamlichi, "Comparative study of five different methods of adjustment by the Weibull model to determine the most accurate method of analyzing annual variations of wind energy in Tetouan–Morocco," *Proc. Manuf.*, vol. 46, pp. 698–707, Jan. 2020, doi: 10.1016/j.promfg.2020.03.099.

[25] F. Knidiri, A. Laaouina, M. Fabre, and A. Wyatt, "L'énergie éolienne au maroc: Gisement—Dimensionnement," Renew. Energy Develop. Center, Ministry Energy Mines, Morocco, Tech. Rep. 86-0109, 1986.

[26] C. G. Justus and A. Mikhail, "Height variation of wind speed and wind distributions statistics," *Geophys. Res. Lett.*, vol. 3, no. 5, pp. 261–264, May 1976, doi: 10.1029/GL003i005p00261.

[27] A. Spera and T. R. Richards, "Modified power law equations for vertical wind profiles," Dept. Energy, Lewis Res. Center, NASA, Washington, DC, USA, Tech. Rep. DOE/NASA/1059-79/4, Jun. 1979, p. 12.

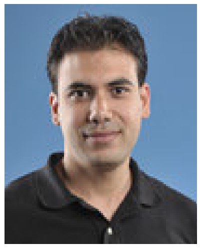
[28] L. Bauer. *Base de Données sur les éoliennes*. Accessed: Apr. 29, 2023. [Online]. Available: https://fr.wind-turbine-models.com/turbines

[29] I. Khan, Z. Li, Y. Xu, and W. Gu, "Distributed control algorithm for optimal reactive power control in power grids," *Int. J. Electr. Power Energy Syst.*, vol. 83, pp. 505–513, Dec. 2016, doi: 10.1016/j.ijepes.2016.04.004.

[30] R. Ranjan and Das, "Simple and efficient computer algorithm to solve radial distribution networks," *Electr. Power Compon. Syst.*, vol. 31, no. 1, pp. 95–107, Jan. 2003, doi: 10.1080/15325000390112099.

[31] M. Tolba, H. Rezk, V. Tulsky, A. Diab, A. Abdelaziz, and A. Vanin, "Impact of optimum allocation of renewable distributed generations on distribution networks based on different optimization algorithms," *Energies*, vol. 11, no. 1, p. 245, Jan. 2018, doi: 10.3390/en11010245.

FATIMA-AZAHRAA BOURHIM received the master's degree in renewable energy and storage from the Faculty of Science, Mohammed V. University, Rabat, Morocco, in 2018, where she is currently pursuing the Ph.D. degree with the Laboratory of Condensed Matter and Interdisciplinary Sciences, Science and Technology Centre. Her research activities are centered on wind energy technology optimization, wind energy grid integration, and artificial neural networks.



AHMED OUAMMI received the Ph.D. degree from the Polytechnic School, University of Genoa, Italy, in 2010. He was a Research Fellow with the University of Genoa and an Assistant Professor with the National Centre for Scientific and Technical Research (CNRST). He is currently associated with the Department of Electrical Engineering, ETS, Montreal. His research activities include decision support models, control and optimization of smart grids, and microgrids, with special focus on the implementation of original methods, models, and optimal control algorithms, with applications to cooperative and interconnected smart systems integrated renewable energy systems.

RACHID BENCHRIFA was a Researcher with the National Center of Scientific and Technical Research (CNRST-Morocco), Rabat, Morocco. He was a Co-Founder of the Unit of Renewable Energy Economy and Technologies (TEER), CNRST, in 1995. Currently, he is with the Faculty of Sciences, Mohammed V. University, Rabat, and a member of the Laboratory of Condensed Matter and Interdisciplinary Sciences. He has authored and coauthored many papers, conferences, and books on both renewable energies and thermal energy storage systems.

MOHAMED CHAOUCH received the Ph.D. degree in mathematics from the University of Dijon, France. He is currently an Associate Professor of statistics with Qatar University. Previously, he was a Research Engineer of data science with Electricite De France, EDF Research and Development. His specialization is in massive data analytics, functional data analysis, and statistical learning with application to electricity demand and renewable energy generation within the smart grid context.