Hybrid neurofuzzy wind power forecast and wind turbine location for embedded generation

Paul A. Adedeji *[a], Stephen A. Akinlabi [b], Nkosinathi Madushele [a], Obafemi O. Olatunji [a]

[a] Department of Mechanical Engineering Science, University of Johannesburg, South Africa.
[b]Department of Mechanical Engineering, Walter Sisulu University, South Africa.

*Corresponding author: pauladedeji2k5@gmail.com

Abstract

Wind energy uptake in South Africa is significantly increasing both at micro and macro level and the possibility of embedded generation cannot be undermined considering the state of electricity supply in the country. This study identifies a wind hotspot site in the Eastern Cape province, performs an *in silico* deployment of three utility-scale wind turbines of 60 m hub height each from different manufacturers, develops machine learning models to forecast very short-term power production of the three wind turbine generators (WTG) and investigates the feasibility of embedded generation for a potential livestock industry in the area. Windographer software was used to characterize and simulate the net output power from these turbines using the wind speed of the potential site. Two hybrid models of adaptive neurofuzzy inference system (ANFIS) comprising genetic algorithm (GA) and particle swarm optimization (PSO) each for a turbine were developed to forecast very short-term power output. The feasibility of embedded generation for typical medium-scale agricultural industry was investigated using a weighted Weber facility location model. The analytical hierarchical process (AHP) was used for weight determination. From our findings, the WTG-1 was selected based on its error performance metrics (root mean square error of 0.180, mean absolute standard deviation of 0.091 and coefficient of determination of 0.914 and CT= 702.3 *s*) in the optimal model (PSO-ANFIS). Criteria were ranked based on their order of significance to the agricultural industry as proximity to water supply, labour availability, power supply and road network. Also, as a proof of concept, the optimal location of the industrial facility relative to other criteria was $X = 19.24m, Y = 47.11m$. This study reveals the significance of resource forecasting and feasibility of embedded generation, thus improving the quality of preliminary resource assessment and facility location among site developers.

Keywords: ANFIS; embedded generation; genetic algorithm; particle swarm optimization; single facility location; South Africa; utility-scale wind turbine; wind energy.

Nomenclature	
a_i	Quantity of resources to be shipped
c_1	Particle cognitive acceleration
c_2	Particle social acceleration
c_T	Total cost
$gBest$	Best swarm position
m	Number of resources to be shipped
O_j^1	Output of adaptive node *j*.
p_j	Particle position vector

$pBest$	Best particle position
P_{ij}	Pairwise comparison matrix
$\overline{P_{ij}}$	Normalized pairwise comparison matrix
v_j	Particle velocity vector
(x_i, y_i)	Distance from source i to plant
(X, Y)	Plant location
$\bar{y}$	Average wind power output, MW
y_k	Observed wind power output, MW
$\widehat{y_k}$	Predicted wind power output, MW
μ_{A_j}	Membership function of fuzzy set A.

1. Introduction

About 13 % of the global population (largely sub-Saharan Africa and South Asia region) still live without access to electricity [1] and last mile connectivity to the grid or off-grid supply still remains a problem in many developing countries. This statistic largely comprises the sub-Saharan Africa and South Asia regions. Similarly, 40 % of the global population do not have access to clean fuels and technologies for cooking [1]. Consequently, household air pollution from the use of solid biomass, coal, and kerosene for cooking accounts for about 4 million death a year with women and children mostly affected [1], [2]. Among the sub-Saharan African countries, South Africa occupies the upper strata among countries with high prospects for renewable energy resources in their energy mix [3], [4]. South Africa largely depends on coal for power generation, which accounts for about 95 % of the electricity generated in the country [5]. However, in the last decade, the country has experienced an increase in the growth of renewable energy resources in the national energy mix with wind and solar energy increasing in exploration.

Renewable energy pathway in South Africa was initiated with the Integrated Resource Plan (IRP) developed by the Department of Energy in 2010 and gazetted in 2011. The target of 17,800 MW to be derived from the renewables using wind, solar photo-voltaic(PV), and concentrated solar power (CSP) sources [6] by 2030 has influenced a rapid growth of these renewable sources in the country. This initiated the Renewable Energy Independent Power Producer Procurement Programme (REI4P) established towards procuring the new power generation capability. Wind and solar sites were marked out by this programme to present spaces of extrastatecraft for wind and solar energy developers, thus increasing the percentage of the renewables in the country's energy mix.

Wind resource assessment is indispensable in evaluating the wind power utilization in a wind energy-rich site [7], [8]. The integrity of the assessment often determines the viability of the investment most especially in large-scale harvesting. Wind data are collected from identified area for a long period of time in order to study the seasonality, trend and establish variability of the resource in the site for the purpose of strategic, operational and installation planning. The wind characteristics are investigated to ensure viability of the investment either on a large or medium-scale and also determine which location specifically yields abundance of the wind resource. Wind speed is observed to increase significantly with height [9] and this is governed by the wind shear phenomenon. This elevation in turn determines the harvestable amount of power by a wind turbine. Wind measurements are often carried out at heights lower than the potential hub heights and so the extrapolation technique using the $1/7^{th}$ power law and the wind shear coefficient is used in this process [10].

Non-linearity and non-stationarity of wind speed data have made them very difficult to estimate. Estimates with numerical methods have not been able to accommodate imprecisions and fuzziness in real-time wind data. However, the introduction of machine learning techniques has improved accuracy, computational speed, model complexity and data veracity [11]. Machine learning approaches are widely known for the ability to learn latent patterns within an avalanche of data for the purpose of information deduction, and intelligent decision-making. The adaptive neuro-fuzzy inference system (ANFIS) is one of the prominent techniques in this class. ANFIS integrates artificial neural network (ANN) and fuzzy logic (FL) modeling approaches to solve non-linear problems. While ANN model acquires its knowledge during the learning process, knowledge acquisition in the FL model is hinged to their rules and the rule definition forms one of the herculean tasks in its modeling [12]. Forming the rule base becomes more complex when the number of variables increase. ANFIS modeling technique first developed by Jang [13] uses the derivative training technique. Here, the antecedent is trained using a gradient descent backpropagation method and the consequence obtained using least square estimation. It is expected that a highly efficient ANFIS model should possess the following features: fast learning, on-line adaptability, self-adjusting capability towards achieving global minimum of error, and less computational complexity [11], [14]. Based on the training technique, ANFIS training can be online or offline depending on the model of data presentation to the model during the training process. In online training, the model is presented with new data for training to increase the accuracy. On the contrary, the offline training presents the same dataset to the model repeatedly for training until a lower network error is achieved and model overfitting is avoided [19]. ANFIS training based on the antecedent and consequent parameter optimization is classified into hybrid, derivative, and heuristic-based training [20]. However, for the purpose of parameter tuning towards achieving optimality in these identified features and minimizing the local minimum condition, ANFIS models are often hybridized with evolutionary algorithms like particle swarm optimization (PSO) [15], [16], differential evolution (DE) [17] and genetic algorithm (GA) [18].

The non-derivative population-based optimization models have been most preferred in the literature as a hybrid of ANFIS modeling for improved accuracy as alluded to by Karaboga and Kaya [23]. Among the models within this class, GA and PSO have been preferred in many studies even for the optimization of other models asides ANFIS [24] due to their robust search methodology for global optimal values of model parameters and more advantageous is the PSO optimization due to its notable accuracy and reduced computational time [25], [26]. For instance, Khosravi et al. [18] investigated the effectiveness of some selected machine learning algorithms for short-term wind speed forecast, ANFIS-PSO and ANFIS-GA were considered. The study compared the performance of these models on multi-interval hold-out data of which one of the models that ranked the best is the ANFIS-PSO with the other models being group method of data handling (GMDH) and multilayer feedforward neural network (MLFFNN). Also, Hossain et al. [21] investigated a hybrid of ANFIS with PSO, GA and DE for the forecast of monthly and weekly wind power density in three wind farms. The performance of each model was evaluated using the root mean square error (RMSE), mean absolute bias error (MABE), mean absolute percentage error (MAPE) and the coefficient of determination (R^2). In all the wind farms considered in the study, the least errors were recorded for ANFIS-PSO and followed by ANFIS-GA. The first of the double stage wind power predictive model proposed by Eseye et al. [22] uses a hybrid of ANFIS-GA to predict wind speed of a microgrid wind farm. The second stage of the model maps the actual wind speed and its relative power. An average MAPE of 6.87, RMSE of 13.85, average sum squared error of 67.84 and average standard deviation of error (SDE) of 13.57 were reported for daily forecast of the four seasons of the year. Even though the study accounted for error deviations of the forecast and the predicted, model accuracy measures were not considered, thus, leaving the reliability of the model unknown. From all the studies considered, it was observed that the resource forecasts were based on existing wind power generating facilities. By implication, data for the studies were obtained from the supervisory control and data acquisition (SCADA) system. This approach has helped in proffering a better understanding of the resource for a developed site. Conversely, similar studies proffering a better understand the resource intermittency and variability prior to site development is sparse in the literature.

The state of electricity supply most especially in developing countries have necessitated a decentralized system with an unbundling of the power generation, transmission and distribution sector. One of the sectors which suffers most in erratic power supply is the manufacturing sector. Manufacturing industries are often associated with energy intensive equipment which makes the consumption from this sector relatively higher than other sectors. In countries where fluctuations in electricity supply is largely prevalent, encouragement has been given to manufacturing industries to practice embedded generation. This involves the generation of electricity connected to a distribution network but generated close to the point of use [27]. This paradigm shift from complete national grid dependency to embedded generation is known to minimize transmission losses, costs of construction of substations and transmission towers, environmental impacts in terms of land clearing and felling of trees for construction of transmission lines, influence grid stability via avoidance of excess supply of energy to the grid but rather to satisfy a load demand, sometimes revenue generation as excess generation could be sold out and energy reliability as generation can be controlled by the power station.

There exists a dilemma in embedded generation using renewables; the criteria for the facility location to ensure viability of the investment and locating the facility in an area with abundance of the energy resource because renewable energy sources are geospatial. These two challenges make the problem a multi-attribute facility location problem (MAFLP). Facility location problems are location science problems which involve optimal location of specific facility relative to other facilities [28], thus minimizing cost of travel and maximizing investment profit. This could be a facility location-allocation problem or a location decision problem [29], [30]. For a single facility location problem, the simple Weber model [31] still remains highly relevant. The author solves the problem of locating a factory with two localized raw materials location and a market as a shipping point for products leading to a locational triangle. Several optimization models have been developed under this basis for multi-facility systems with further constraints.

Resource forecast in wind energy studies has increased significantly in the literature with the use of soft computing techniques like ANFIS gaining more significance. This is due to inherent variability, intermittency and complexity of wind resource forecast and the need for improved strategic and operational planning prior to wind site development. Further to this, many authors [18], [21], [32] have alluded to the inaccuracy of single models for forecast and have proposed hybrid models of ANFIS technique for resource forecast. In response to this, population-based optimization techniques have been widely used as a hybrid of ANFIS model for parameter tuning towards improved model accuracy. However, asides the use of these models on existing sites, investigative resource forecast towards ensuring resource abundance in a proposed site for wind energy exploration prior to site development has been given less attention and this may negatively affect investment viability, most especially when large-scale exploration of wind resource is involved. Also, with the increasing support for embedded generation, it is essential that consuming facility for wind power generated on a proposed wind power generation site must be closer to the point of generation to minimize cost of transmission, environmental impact of transmission (e.g. impacts on avian habitat), and transmission losses. It is believed that investigating the feasibility of embedded generation for a viable industry in the selected location will further improve energy reliability and strategic planning for future upscaling of power generation towards meeting demands. Hence, this study (i) performs an *in silico* deployment of three utility-scale wind turbines from three different manufacturers: Vestas, Enercon and Nordex to a potential wind-rich site in the Eastern Cape of South Africa. (ii) performs a resource forecast in the selected site using GA-ANFIS and PSO-ANFIS models (iii) performs criteria ranking of criteria essential for locating the selected wind turbine using AHP approach, (iv) investigates the suitable location of the wind turbine relative to other siting constraints towards embedded generation using the weighted Weber model developed. While this section of the study presents a background to the study, section 2 describes the methodology adopted for the wind resource assessment, the resource forecast, criteria ranking and the facility location. Section 3 presents the results obtained both for the machine learning modes and the facility location model, and section 4 concludes the study.

2. Methodology

This section presents the methodology used in this study for wind resource assessment, model development and model evaluation.

2.1. Wind resource characterization

Siting a wind farm requires assessment of the wind resource for technical and economic feasibility [33]. The process of determining these feasibilities is referred to as wind resource assessment (WRA). The WRA process is both an expensive and time-consuming process. In investigating the wind energy potential of a geographical location, meteorological mast is mounted with anemometer, wind vane and meteorological devices for measuring pressure, humidity, and ambient temperature. It is ensured that these devices are enabled with data-logging facilities to aid in logging the measured variables in real time for further analysis. Usually, data from variable heights at 10m, 20m, 50m, 80m, and 100m above the ground level are measured on the potential wind farm site.

The capital-intensive nature of the WRA process often results into prior-analysis of the wind power potential of the proposed site. Wind data obtained could be tested against the proposed model of the wind turbine to be installed both for feasibility studies and strategic planning purposes. In this study, data obtained at a height of 60m above the ground level on which the mast is mounted was analyzed on three utility-scale wind turbines from different manufacturers. It was ensured that the hub heights of the selected wind turbines are within the range of the heights from which measurements were taken in the potential site.

The Windographer Professional License software (Version 4.1.14) was used in the WRA process. The software takes the collected meteorological data as inputs. Data correction in terms of units and tabulation was performed to ensure that the units of measurement from the meteorological mast is in congruence with that in the software.

Shown in Figure 1-3 are the wind characteristics of the site. Figure 1 shows the wind rose with more wind coming from 315°. Figure 2 shows the wind distribution which is best fitted by a Weibull distribution with parameters $k = 1.97 \; and \; A = 9.08 \frac{m}{s}$. Figure 3 shows the monthly wind distribution of the site. Maximum wind resource is obtained in September and the least in February. There was no record for the month of April which might be due to device maintenance or other instrumental factors.

Table 1. Technical specifications of the wind turbines models experimented

2.2.Data collection

Wind speed data used in this study was obtained from the wind atlas of South Africa (WASA 2). The data, with a resolution of 10mins was collected with cup anemometers mounted at 60m in Rhodes, Eastern Cape, South Africa at 28.07351ºE, 30.81436ºS over a period of 12months. Eastern Cape Province is one of the provinces with the highest wind energy resource in South Africa [34]. The wind map of the area was developed using ArcGIS 10.4 with a resolution of 30 x 30 m as shown in Figure 4.

2.3.Model development

2.3.1. The adaptive neurofuzzy inference system structure

The ANFIS model is an integrated model comprising ANN and FL. The model comprising the two topologies produces a five-layered structure capable of dual learning with increased performance even when imprecision and uncertainties exist in the system being modeled. ANFIS model possesses two adaptive layers (first and fourth) and three fixed layers (second, third and fifth). The first layer being the fuzzy layer consists of fuzzy membership functions. The firing strength of each rule is computed at the second layer using a multiplicative operator. The third layer of the model normalizes the firing strength at nodes of the ANFIS model using a ratio of individual firing strength to an aggregate. The defuzzification process to determine the effect of a rule on the model output is performed at the fourth layer while the fifth layer uses an aggregation function to determine the overall model output. The synergy between the layers is shown in Figure 5. Rule formation in ANFIS model follows the first order Takagi-Sugeno fuzzy model. For instance, for a model with inputs X_1 and X_2, and node parameters, p_j, q_j, r_j; the rule structure becomes:

Fuzzy Rule 1: If X_1 is A_1 AND X_2 is B_1 then $f_1 = p_1 X_1 + q_1 X_2 + r_1$.

Fuzzy Rule 2: If X_1 is A_2 AND X_2 is B_2 then $f_2 = p_2 X_1 + q_2 X_2 + r_2$.

From the ANFIS structure in Figure 5, every node in the first layer are adaptive and each adapts to a function parameter [35]. Each node consists of fuzzy membership function whose output function is calculated from:

$$O_j^1 = \mu_{A_j}(I_1), j = 1, 2 \tag{9}$$

$$O_j^1 = \mu_{B_j}(I_2), j = 1, 2 \tag{10}$$

At the second layer, which has all nodes non-adaptive, the firing strengths of each rule is evaluated from a multiplicative operator according to Eqn. (11).

$$O_j^2 = w_j = \mu_{A_j}(I_1) . \mu_{B_j}(I_2) \quad , j = 1, 2 \tag{11}$$

Similarly, the third layer comprises of non-adaptive nodes. In this layer, normalization of the firing strength, $\overline{w_i}$ in the jth node is performed using the ratio of the jth firing strength and the aggregate of all firing strengths from all rules according to [35]:

$$O_j^3 = \overline{w_j} = \frac{w_j}{w_1 + w_2} \qquad j = 1, 2 \tag{12}$$

The fourth layer, however, has all nodes adaptive and it performs defuzzification. Here, the influence of jth rule on the layer output is expressed according to Eqn. (13) and the parameters of the nodes are represented with p_j, q_j, r_j.

$$O_j^4 = \overline{w_l} \left(p_j I_1 + q_j I_2 + r_j \right) = \overline{w_l} z_j \tag{13}$$

The fifth layer is another layer with all nodes non-adaptive. Here, aggregation of all the in-coming signals from the other previous layer though a summing function [36]:

$$O_j^5 = \sum_j \overline{w_\iota} z_j = \frac{\sum_j w_j z_j}{\sum_j w_j} \tag{14}$$

2.3.2. The GA-ANFIS modeling

The genetic algorithm (GA), which evolved from the theory of biological evolution uses the principle of natural selection and genetics to find solution to a problem within a search space [37]. The technique is one of the oldest and most-widely used population-based optimization techniques, which operates on three genetic principles of selection, crossover and mutation [38], [39]. GA technique applies the principle of survival of the fittest to produce problem solutions such that each generation is an improvement on the previous generations. Every individual in the population competes for their right to reproduce, however, this favours members that maximizes the value of a fitness objective function. Such individuals then proceed to the next generation to reproduce and this process continues in an iterative manner. At first, a definite number of prospective solutions are generated from random parameter values. Each candidate solution is screened according to a fitness function to determine which offspring goes to the next generation and which does not. Breeding, through a recombination of operators like crossover to simulate the fundamental biological cross-fertilization and mutation [40]. The mode of operation of the three genetic operators are briefly discussed below [38]:

Selection Technique: The best chromosomes in the population which represents the best solutions are identified through an evaluation of the fitness function for each chromosome. These chromosomes serve as parents for the new generation of offspring.

Crossover Technique: Through this technique, hybrid offspring resulting from a crossbreeding between two parents are produced. This thus gives offspring with better fitness compared to their parents. The crossover technique determines the structure and child to parent chromosome and is implemented using several techniques like cycle order, uniform, tournament, partially mapped, ranking selection, ordered, N-point, diagonal crossover and so on [41].

Mutation Technique: This technique searches for new solutions within the available search space such that the local optimum solutions are not taken as global optimum solutions. In achieving this, genes inside some of the chromosomes are changed according to a random order.

A GA-ANFIS hybrid model with offline training was performed on gross power output of three wind turbines hypothetically deployed to the site with a placemark in Figure 4. The model procedure is described in the flowchart shown in Figure 6. The model parameters and characteristics are also presented in Table 2.

Table 2. Model characteristics for GA-ANFIS model

2.3.3. PSO-ANFIS modeling

The particle swarm optimization technique is developed from the behavior of social organisms that occur in groups like birds, fish, and ants. The optimization technique leverages the information sharing characteristics of these organisms. Its mode of operation is similar to that of the genetic algorithm, however, rather than focusing on single individual implementation, the PSO technique considers a population of individuals in the form of a swarm. The whole population of the swarm is moved in search for the optimal solution rather than an individual movement observed in GA model [42]. Within the swarm, each particle has two distinct properties; its velocity and position. The technique examines each property to determine the best solution using the present swarm and moves the swarm to the new optimal position. Each particle tends to move in a random manner along two influences; its best achieved position and the best achieved position of the swarm [16], [32]. Thus, a particle j defined by a position vector, p_j and velocity vector, v_j undergoes iterative process which changes its position to ${p_j}^{t+1}$ and velocity to ${v_j}^{t+1}$ according to:

$$ {v_j}^{t+1} = \omega {v_j}^{t} + c_1 r_1 \left(pBest_j^t - {p_j}^{t}\right) + c_2 r_2 \left(gBest_j^t - {p_j}^{t}\right) \qquad (1) $$

$$ {p_j}^{t+1} = {p_j}^{t} + {v_j}^{t}.t \qquad (2) $$

where $pBest$ and $gBest$ are the best particle individual position and the best swarm position respectively. Parameters $c_1, and\ c_2$ are two positive constants, $r_1, and\ r_2$, random constants between 0 and 1 and ω is the inertia weight. The PSO optimization technique has less number of parameters to tune and constraints acceptance, which is its major advantage compared to other derivative-free techniques [43]. The global optimal solutions are used for the ANFIS parameters, thus tuning the ANFIS model. The flowchart of this process as followed in this study is shown in Figure 3 and the model parameters and characteristics are presented in Table 3.

Table 3. Model characteristics for PSO-ANFIS model

2.4.Facility location with embedded generation

Energy forms a very vital component in the profitability of manufacturing systems. The unreliable power situation in Africa as a whole as influenced the industrialization rate and the tenancy of many investors. Many manufacturing industries are associated with energy-intensive processes and thus, consumes more energy at large scale compared to other sectors of a nation. As part of this panacea, embedded generation of electricity is now being encouraged by many countries among energy-intensive industries such that energy generated at the national level can be distributed across other sectors, thus increasing energy availability and sustainability [4]. South Africa is one of the highly industrialized countries in Africa with manufacturing industries having contributed 4.4 % to the country's economy in 2018 [44]. However, manufacturing companies have been grossly affected by the increased frequency of load-shedding in the country. This have reduced the productivity of such companies and embedded generation then becomes a viable option. The Eastern Cape province, which represents 13.9 % of the South African land mass is highly notable for the automotive and the agricultural industries [45]. Several criteria are involved in the location of automobile industry many of which centres around maximizing profit and minimizing overall cost. Some of these criteria include:

i. Proximity to raw materials
ii. Proximity to labour
iii. Proximity to transportation and communication network.
iv. Land availability
v. Proximity to power supply
vi. Proximity to market
vii. Proximity to banking and credit facilities
viii. Proximity to maintenance facilities
ix. Proximity to fire-fighting services

With these mentioned, siting an automobile industry close to the location for which the data was collected (Figure 4) to harness the abundance of wind energy may only fulfill some of these criteria and not others like (vi) to (ix). However, many of these criteria are not needed to site an agricultural industry. It should be clearly stated that the location considered for the wind abundance in this study is of high elevation and mountainous, hence, this supports livestock farming compared to the crop farming. Therefore, the possibility of siting powering a large-scale livestock farm within the area with the wind turbine was investigated.

Wind energy is highly abundant in this province and can be harnessed by the automotive or agricultural sector of the province. From this study, the WTG-1 was recommended due to its high capacity rating and based on the least error of the model developed for its forecast, thus providing a near accurate prospective power generated for economic planning.

Problem definition

Asides the feasibility of the proposed turbine for the operation of a typical medium-scale livestock industry, several criteria are required to be considered in the siting of the farm near the wind turbine location specified in Figure 4. This becomes that of single-facility location problem. For the typical livestock industry the following assumptions were made:

i. Power consumption demand can be satisfied by $n + 1$ turbines where $n \geq 1$.
ii. The spatial location of the turbine(s) is free from environmental interference (e.g. interference with important bird areas, not close to the airport, protected areas etc.).
iii. There is low wind resource intermittency and variability in the area.
iv. The battery storage system is efficient for off-peak periods and conditions of turbine cut-off speed.

Solution

The solution to this model was approached to using the simple Weber model [31], [46] which seeks to locate a production plant with location (X, Y) such that the total costs, C_T is minimized. The costs are expressed as a function of the quantity of m resources, a_i shipped from sources and the distance, (x_i, y_i) of the source to the facility location. The model follows the Euclidean distance function and is expressed mathematically:

$$Minimize\ C_T = a_i \sqrt{\sum_{i=1}^{m} (X - x_i)^2 + (Y - y_i)^2} \quad (3)$$

Minimizing the weighted squared distance by squaring (3) thus removes the radicals, thus becoming a centre of gravity problem. The Eqn. (3) then becomes:

$$Minimize\ C_T = a_i \sum_{i=1}^{m} (X - x_i)^2 + (Y - y_i)^2 \quad (4)$$

By the way of derivatives in calculus, an optimal solution for (4) becomes:

$$X = \frac{\sum_{i=1}^{m} a_i x_i}{\sum_{i=1}^{m} a_i} \tag{5}$$

$$Y = \frac{\sum_{i=1}^{m} a_i y_i}{\sum_{i=1}^{m} a_i} \tag{6}$$

For the medium-scale livestock industry considered in this study, it is expedient to consider the following facilities based on technical premise [47].

i. The power supply (wind turbine(s)) (a_1, x_1, y_1)
ii. Road network (a_2, x_2, y_2)
iii. Water supply(a_3, x_3, y_3)
iv. Labour availability (distance to the nearest city) (a_4, x_4, y_4)

The solution then becomes:

$$X = \frac{a_1x_1 + a_2x_2 + a_3x_3 + a_4x_4}{a_1 + a_2 + a_3 + a_4} \tag{7}$$

$$Y = \frac{a_1y_1 + a_2y_2 + a_3y_3 + a_4y_4}{a_1 + a_2 + a_3 + a_4} \tag{8}$$

By introducing weight criteria, w_i $(i = 1 \ldots 4)$ to each criterion, the solution then becomes

$$X = \frac{w_1a_1x_1 + w_2a_2x_2 + w_3a_3x_3 + w_4a_4x_4}{a_1 + a_2 + a_3 + a_4} \tag{9}$$

$$Y = \frac{w_1a_1y_1 + w_2a_2y_2 + w_3a_3y_3 + w_4a_4y_4}{a_1 + a_2 + a_3 + a_4} \tag{10}$$

Some techniques have been developed for criteria ranking like analytical hierarchical process (AHP) method [48], [49], technique for order preference by similarity to ideal solution (TOPSIS) [50], fuzzy modelling technique [51], [52]. However, AHP has been mostly used in many studies due to its simplicity, easy computation, ability to follow intuitive problem solving technique and its ability to integrate qualitative and quantitative criteria [53], [54]. Hence, in this study we use AHP technique developed by Saaty for ranking of the criteria. The technique uses the pairwise comparison matrix whose values are obtained from the literature and expert judgement. In computing the pairwise comparison matrix, the Saaty's ranking scale of 1-9 was used with the definitions of values presented in Table 4.

Table 4. Saaty's ranking scale [55]

The AHP procedure was computed as follows:

i. The pairwise comparison matrix of $n \times n$ was designed consisting of n criteria according to the Saaty's integer value scale. It was ensured that the property $P_{ij}.P_{ji} = 1$ was satisfied.

ii. A normalized pairwise comparison matrix, $\overline{P_{ij}}$ was computed such that the aggregate of each column is 1. This was performed using:

$$\overline{P_{ij}} = \frac{P_{ij}}{\sum_{i=1}^{n} P_{ij}} \tag{11}$$

iii. The relative weight of each criteria was computed from Eqn. (12). The value of the weights signifies the degree of influence of each criterion on the location of the agricultural farm.

$$w_i = \frac{\sum_{i=1}^{n} \overline{P_{ij}}}{n} \tag{12}$$

iv. A consistency test was performed on the matrix to ensure that the subjective inconsistencies are eliminated. The consistency ratio, CR was evaluated using:

$$CR = \frac{CI}{RCI} \tag{13}$$

where $CI = \frac{\lambda_{max} - n}{n-1}$ (14)

The location of the livestock industry was further evaluated relative to other criteria using the weighted Weber model and a spatial diagram of its location relative to other supporting services were drawn.

3. Results and discussion

The model was trained and tested with 6months data and data division was 70:30: 70 % of the data (12,195 data points) was used for training and 30 % (5,226 data points) of the data used for testing. It was ensured that the same model parameters were used for the three turbines to avoid bias in results. The GA-ANFIS and PSO-ANFIS models were computed in MATLAB (R2015a) installed a computing device with configuration 64 bits, 32GB RAM Intel (R) Core (TM) i7 5960X. Due to the volume of the test data, only the statistical performance metrics used for model evaluation were presented.

3.1.Model performance evaluation

As a measure of error deviations, the root mean square error (RMSE), mean absolute deviation (MAD) were used. To evaluate the robustness of the model, the coefficient of determination (R^2) was used and calculated using Eqn. 15-17 [35]. The computational time was also used to evaluate the model efficiency and reported in Table 2.

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N}[y_k - \widehat{y_k}]^2}{N}} \tag{15}$$

$$MAD = \frac{1}{N}\sum_{k=1}^{N}|y_k - \bar{y}| \tag{16}$$

$$R^2 = 1 - \left[\frac{\sum_{k=1}^{N}(\widehat{y_k} - y_k)}{\sum_{k=1}^{N}(\widehat{y_k} - \bar{y})}\right] \tag{17}$$

where y_k is the observed wind power, $\widehat{y_k}$ is the predicted wind power and $\bar{y}$ is the mean of wind power.

3.2.Model results

Presented in Table 5 is the model results for both GA-ANFIS and PSO-ANFIS for the three utility-scale wind turbines with the wind turbine power output measured in megawatts (MW).

Table 5. Statistical performance evaluation of the three wind turbines

3.2.1. GA-ANFIS Modeling

From Table 5, the least forecast error measurements (RMSE and MAD) were obtained from WTG-1. The RMSE measures the quality of fit between the observed and predicted turbine power output. The variation between the error metrics is a result of differences in the turbine capacities. This variation, however does not speak of the quality of the turbines in operation but rather a spread in the error between the forecast and the observed wind turbine if the turbine is used on the site and the model is used for forecast. From Table 1, WTG-1 has the highest rated capacity of 1.8 MW and also recorded the least value of error measurement ($RMSE = 0.184 \; and \; MAD = 0.091$) even though the turbine has the least value for coefficient of determination ($R^2 = 0.909$). However, due to its least error value, it can be recommended as most preferred among the three turbines for the area. Despite the large wind power obtained for WTG-1, its model recorded the least computational time ($CT = 984.1 \; secs$). Based on the above performance metrics, WTG-1 is preferred above others.

3.2.2. PSO-ANFIS Modeling

Table 5 also presents the results obtained from the PSO-ANFIS model for the three utility-scale wind turbines. Error analysis between the actual and predicted power output shows a variation between the results of the three turbines. Error values are the lowest for WTG-1 both for the RMSE and MAD ($RMSE = 0.180$ and $MAD = 0.091$). However, as a measure of model accuracy, the highest coefficient of determination was recorded for WTG-2 ($R^2 = 0.962$ and least for WTG-3 ($R^2 = 0.905$). Based on computational efficiency, the least computational time was recorded for model developed for WTG-3 ($CT = 701.1$ $secs$) and the highest for WTG-2 ($CT = 723.1$ $secs$). It should be declared that the same amount of data and model architecture were used for the three wind turbines. Based on the model performance, there exists a significant error difference between the error metrics of WTG-1 and the other two turbines. Even though WTG-2 records the best R^2, it also records the highest computational time. However, a comparison between the WTG-1 and WG-3 shows a slight variation in R^2 and CT. Hence, WTG-1 can be preferred over the other turbines based on the presented metrics.

On the overall, based on model efficiency and effectiveness, the PSO-ANFIS model records a significantly lesser computational time compared to the GA-ANFIS model and so should be selected for forecast towards strategic planning of the facility with which the wind turbine is to be utilized. This further demonstrates the computational efficiency of the PSO-ANFIS model. In terms of error measurement, PSO-ANFIS model for the WTG-1 also outwits the GA-ANFIS counterpart, but the R^2 is on the contrary even though slight. Comparing the CT of both models for WTG-1, the PSO-ANFIS model evaluates faster, thus translating into a shorter machine utilization time and lower machine utilization cost. Therefore, selection based on model, the PSO-ANFIS is more preferred and based on the turbine output power, the WTG-1 should be selected, even though more criteria like equipment and installation costs, maintainability, durability and so on should be considered.

It was best to compare the effectiveness of the selected optimal model (WTG-1 (PSO-ANFIS model) with similar studies which used same unit for wind power in the literature, hence we present Table 6. The proposed model in this study when compared with [22] and [56] shows a lesser RMSE value. This could be due to the varying choice of model parameters for the hybrid ANFIS models. On the contrary, the model proposed by [32] slightly outperforms that proposed by this study by a lesser error performance metrics and a slightly higher accuracy. Despite this, it could be safely said that the selected model in this study performs effectively.

Table 6. Performance comparison of this study with other studies

3.3.Facility location with prospect of embedded generation

The pairwise comparison matrix was computed using AHP approach and the AHP computation was performed using a the web-based AHP calculator developed by Goepel [57] . The principal eigen value obtained was 4.170 and the CR being 6.2 % which is less than 10% as the stated by Saaty. Table 7 presents the individual weights and rank of each criterion.

Table 7. Resulting weights and ranks of each criterion.

Hence the facility location solution then becomes:

$$X = \frac{0.143a_1x_1 + 0.044a_2x_2 + 0.669a_3x_3 + 0.144a_4x_4}{a_1 + a_2 + a_3 + a_4} \quad (18)$$

$$Y = \frac{0.143a_1y_1 + 0.044a_2y_2 + 0.669a_3y_3 + 0.144a_4y_4}{a_1 + a_2 + a_3 + a_4} \quad (19)$$

Considering an agricultural farm with the requirements in Table 8. The values were hypothetically selected for a proof of concept.

Table 8. Distance and unit cost per unit distance relative to resource utilization

By substituting the values in Table 8 into Eqn.6, the livestock industry can be located at $X = 19.24m, Y = 47.11m$. The location of the facility relative to other criteria is shown in Figure 8. It can be observed that this location is closer to the water supply, the closest road network and the power supply than the nearest city as source of labour.

4. Conclusions

Wind energy is one of the most inexhaustible renewable energy resources. It has high resource availability unlike the solar resource, which is only available during the day time and during sunny days. Resource forecast is essential for the strategic planning and machine learning techniques have been efficient in this domain. Moreover, embedded generation is increasingly gaining traction in manufacturing industries owing to increasing energy demand to satisfy the product demand along the supply chain. This has not only decreased the demand placed by manufacturing industries on the grid but also reduced cost of production. This study assessed the wind speed obtained in the selected site, performed a very short-term forecast of wind power obtained from three wind turbines hypothetically deployed to a wind rich site using GA-ANFIS and PSO-ANFIS models and investigated the feasibility of embedded generation for a potential livestock industry in the area relative to other criteria for siting such industry. From the intelligent forecast, the PSO-ANFIS model performed better than the GA-ANFIS model with lesser forecast error and computational time and hence was preferred for forecast for strategic planning of the power generation. The least error was recorded for WTG-1. Though the choice of wind turbine is influenced by several other factors like cost, reliability, and ease of maintenance etc., however, from this study, based on the error analysis, model accuracy and the turbine capacity, the WTG-1 was most preferred over other turbine models. Also, as a proof of concept, the optimal location of the livestock facility relative to other siting criteria was modeled using a weighted Weber single facility model. Relative to the other criteria, a location of $X = 19.24m, Y = 47.11m$ was obtained for the industry. For further studies, other population-based optimization techniques can be used for ANFIS model optimization and compared for accuracy. Also, the geographical information system (GIS) can be used to determine the prospect of embedded generation in a typical viable facility around an energy source with other vital criteria for facility location considered.

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Figure 1. Wind rose at 60m mean wind speed

Figure 2. Wind distribution of the area

Figure 3. Monthly wind energy statistics of the location.

Figure 4. Wind map of the Eastern Cape Province.

Figure 5. The structure of adaptive neurofuzzy inference system

Figure 6: GA-ANFIS model flowchart.

Figure 7. PSO-ANFIS model flowchart

Figure 8. Location of the livestock industry relative to other criteria (not to scale).