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PREDICTION OF ENERGY GAINS FROM JORDANIAN WIND STATIONS USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT: *System and environmental parameters affecting the output of the wind farm system at different stations in Jordan have been computationally investigated, using artificial neural network (ANN). For the several variables identified, statistical analysis was employed to indicate their relative significance to the targeted output, with the aid of the Pearson's correlation coefficients. ANN shows proficiency in the prediction of the original experimental data for all the stations and turbines. In the simulation, the energy gain increases with the increase in the system and environmental parameters. However, there appears to be a phenomenon of threshold value in the output parameter, which limits the impacts of change in the input parameters on the eventual response of the output. It can be deduced that there is a minimum energy gain value below which increase in any of the system/environmental parameters will not have positive impact on the energy output. Findings show that the turbine characteristics, like rotor diameter and hub height, have more significant impact on the energy gain than the environmental factor like wind speed. The uniqueness of this work is that it predicts the important output of the wind farm system based on the logical arrangement of detailed parameters that are found in all operational units of the system in order to elicit desired effects.*

KEYWORDS: Artificial Neural Network, Wind Farm, Wind Turbine, Energy Gains, Rotor Diameter.

INTRODUCTION

The threats to the environments caused by the global warming have led to several initiatives among stakeholders to proffer alternatives to the use of fossil fuels, which are believed to be the drivers of climate change. Renewable energy from sources like wind, sun and others have been proposed (Lurque et al. 2008; McKendry 2002).

Wind energy is being deployed worldwide, with applications in developed and developing countries (Ammari et al. 2014). American Wind Energy Association (AWEA) estimates that cumulative global wind energy generating capacity topped 147 GW in 2008, and it is said to have been duplicated around five times since 2002, where it was just 31.128 GW (WEC, 2014). Thus, it can be inferred that the ground is fertile for the future of renewable energy, worldwide.

Technical assessments of the performances of wind farms have been reported in literature. Ammari et al. (2014) evaluate the electrical energy derivable from wind at different wind farms in Jordan. Several environmental and systemic factors were considered in their analyses. Environmental factors include mean monthly and annual wind speeds at different geographical locations while the systemic factors include the characteristics of the different wind turbines employed at the different locations. The findings indicate that sites with good wind energy

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show better promise of power output per square meter. Other studies like those of Acker et al. (2007) as well as Rehman et al. (2007) expound the importance of the environmental factor like wind, on the power output. The work of Ammari et al. (2014) was carried out in the context of energy diversification drive of Jordan with inclusion of the eastern part of the country. In the same context, other authors like Bataineh and Dalalah (2013) presents technical assessment of wind power potential at seven different locations in Jordan. Rayleigh distribution was used to model the monthly average wind data at the different locations. Using wind turbines of different capacities, the work estimates energy output potential for the selected sites together with the analysis of energy cost. However, their works are mainly field investigations and there are needs for computational descriptions of these data to explore other salient features of their findings.

Quantitative description of the patterns of the energy gains, Ev, together with the influential factors in the wind farm system, requires a modelling platform that can interpret and assimilate multifarious data of diverse origins with ability to understand behavioural trends in the output quantities, based on the different input variables, and, therefore, predict such trends in the regions behind and beyond the experimental ranges. These mathematical qualities have been demonstrated in Artificial Neural Network (ANN) by several authors (see, e.g., Abidoye and Das, 2015; Abidoye and Mahdi, 2014; Hanspal et al. 2013; Zhang et al. 1998).

The need for modelling platform is also justified by considering the cost and time involved in the experimental investigations of the influences of numerous variables that affect the energy gains from wind turbine. Elaborate experimental investigations might also be laden with inconsistencies as a result of unavoidable experimental errors. Furthermore, many computational techniques are currently available, but the tasks of cost and complexity are almost unavoidable, especially to new users. Such computational techniques often require time-consuming and cost-intensive modelling and simulations, which generally involve complex procedures to set up and run (Hanspal et al. 2013; Spalding 1981; Khudaida and Das, 2014). Thus, there is a need for easy-to-use tools, which are cheap and can easily assist investigators in determining intricate relationships among several interrelated variables. To address these challenges, ANN is chosen in this work to investigate the complex relationships existing among several environmental and system variables that affect the Ev obtained from wind turbines.

ANN is a well-known modeling tool. It possesses the ability to learn and generalize functions from rounds of training as well as extract essential information from data (Abidoye and Das 2015; Khashei and Bijari 2014; Wang and Fu 2008). ANN modelling has the building blocks or elements called ‘neurons’. The neurons are grouped into input, hidden and output layers with respective biases, weights and transfer functions (Abidoye and Das 2015; Yurdakul and Akdas 2013; Mueller and Hemond 2013). The network manipulates the values of the biases and weights in a sequence of training processes and uses the transfer functions to establish the relationships between the inputs and the outputs. ANN modeling techniques have been widely applied in many fields to solve science and engineering problems as well as in medical fields to illustrate medical diagnosis (Amato et al. 2013). It has also been applied to model renewable energy systems, economics, psychology and many more (Abidoye and Das 2015; Kalogirou 1999).

There are complex relationships between energy generation from wind farm system and the influential environmental factors as well as the turbine characteristics. It is widely known that the dynamics of wind turbine behaviour are complex and critical to the optimization of energy gain in wind farm system (Mckay et al. 2014). It is also challenging to identify factors, causing

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desired or undesired effects in the system. The quantification of the effect that these factors have is valuable for making improvements to both power performance and turbine health (Mckay et al. 2014). For some characteristics of the turbine, Capps et al. (2014) find complex and substantial geographical variations in the sensitivity of energy generation. The influences of geographical locations are clearer from the work of Santos et al. (2015) on energy generation from wind across many geographical locations in Iberia. In term of wind potential, high winter potentials are found in high elevation coastal areas. Capps et al. (2014) find high sensitivity of energy generation to rotor diameter, hub height and rated power of the turbines.

Earlier, Mckay et al. (2014) employ neural network to model select wind turbine supervisory control and data acquisition system parameters for an array of turbines from a commercial wind farm that exhibit signs of wake interaction. They also performed Fourier amplitude sensitivity test. They found that parameters like wind speed and rotor rotation frequency are highly influential in power output.

In this work, array of parameters, believed to be instrumental to the optimal performance of the wind farm system, are assembled. The task of analysing these parameters was assigned to ANN, which possesses the capacity to capture non-linear integrating effect in complex relationships between the dependent and the independent variables. This assist in revealing the relative effects of different factors on the energy generation from wind farm system.

It will be shown, later in this work, that the modeling parameters involved in the quantitative descriptions of energy gain (Ev) from wind turbine are interrelated in a complex manner. Since ANN can approximate the relevant functions to the desired accuracy (Zhang et al. 1998; Hanspal et al. 2013), it is therefore believed that logical arrangement and tabulation of the variables will enhance the training, validation, testing as well as prediction of the interrelationships existing among such variables. Thus, according to Hanspal et al. (2013), a well-trained and validated ANN structure can give reliable prediction.

Therefore, this work explores the capabilities of ANN to investigate factors that can promote the energy gains from wind farm system.

METHODOLOGY

After identifying various environmental and system parameters that influence the output of the wind farm system, this work employs statistical modeling tools to describe quantitatively, the effects of these parameters on the amount of energy gains (Ev) from wind turbines of various capacities. Precisely, Multivariate Regression (MVR) in XLSTAT (Microsoft EXCEL) was used for this purpose. Following this, Artificial Neural Network (ANN) in MATLAB (Mathworks Inc., 2011) was employed as the modeling tool. The parameters are logically arranged to elicit desired effects on the targeted outputs. Details of these activities are explained in the following subsections.

Data Sources and Pre-Processing

Data were obtained from the experimental investigations conducted at different stations in Jordan by Ammari et al. (2014). The stations are: Ras Moneef, Azraq south, Safawi, Queen Alia Airport and Aqaba Airport. The aforementioned sites are labelled as A, B, C, D and E in

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the order listed. Geographical coordinates of the stations can be found in Ammari et al. (2014). Their work describes the latitude, longitude and elevation associated with each station.

The variables measured to characterize the above stations include the mean monthly and annual wind speeds at the stations. The investigations were carried out at the height of 10m, at each station. The data were collected for the 12-month period. Data for mean monthly and annual wind speeds at the stations can be found in the work of Ammari et al. (2014).

Wind data for any particular location often come in ranges. As a result, it is generally desirable to present wind data in term of frequency distribution. Ammari et al. (2014) present a probability distribution of the wind data for the above sites, using Weibull probability distribution function with parameters- k (shape parameter) and c (scale parameter). The data are presented in line with seasonal variations- winter, spring, summer and autumn.

Characteristics of different turbines together with their capacities in kilowatt (kW) are important parameters that can offer insight into the energy gain from the wind farm system. This work shows particular interest in these characteristics for the purpose of modelling. The different turbines utilised by Ammari et al. (2014) are named: Fuhrlander (100kW), EWT (500 kW), EWT (900 kW), Fuhrlander (1500 kW), Vestas (3000 kW). Characteristics of these turbines are: Hub height, Swept area, Rotor diameter, Cut-in wind speed, Cut-off wind speed, Rated wind speed, Rated power, and Number of blades. Numeric values for these characteristics can be found in Ammari et al. (2014).

Furthermore, the important output for the purpose of this modelling is the seasonal energy gain (Ev) from the five different wind turbines. Experimental values of Ev at different locations are presented in Ammari et al. (2014).

Non-Linear Regression

The multivariate regression (MVR) analysis is one of the most widely used of all statistical methods. Regression techniques such as principal component regression (PCR) and partial least-squares regression (PLSR), are based on the inverse method (Gosasang et al. 2011; Fox et al. 2011) and they have been widely applied in many fields of study, e.g., anatomy, two-phase flow, energy, etc., (Schumann et al. 2013; Abidoye and Mahdi 2014). In this work, nonlinear regression analysis was performed, using XLSTAT (Microsoft Excel), in order to analyse the principal components of the data and obtain correlation. To enhance the analysis, all categories of data are arranged in a way to relate explicitly the independent variables to the dependent one. From the data of Ammari et al. (2014), the independent variables and the symbols used are: Station parameters: height above sea level (H), Latitude (L), Longitude (N); mean monthly wind speed: January (J), February (F), March (M), April (A), May (May), June (Ju), July (Jul), August (Au), September (Sep), October (Oct), November (Nov), December (Dec), Annual mean wind speed (Am); Seasonal variations of Weibull parameters (k and c) in winter: Kw, Cw; in spring; Ks, Cs; in summer; Km, Cm; in autumn; Ka, Ca. Others are the main characteristic of five different commercial turbines: Hub height (Hh), swept area (Sa), rotor diameter (Rd), cut-in wind speed (VC), cut-off wind speed (VCO), rated wind speed (Vr), rated power (Rp), number of blades (Nb). The dependent or target variable is the energy gain (Ev).

The general linear model of MVR is shown in equation (1),

$$k = bX + e \tag{1}$$

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where k is the predicted output (e.g., energy gain), X is an $n \times m$ matrix of multiple variables such that each row corresponds to the spectra recorded at m wavelengths. The intercept term is accounted for by a column of ones, with X now having $n \times (m+1)$ dimensions. The regression coefficients are contained in the vector $b(b = [bo, b_1, \dots \dots \dots, bn])$, with each corresponding to specific variable in the X matrix. e is the independent error. Similar model is used for PCR and PLSR as shown in equation (2),

$$k = tb + e \tag{2}$$

where t is the principal score vector, calculated as,

$$t = \tilde{X}P \tag{3}$$

where P is the principal component vector. In PLSR, determining the regression coefficients involves calculations, using equation (4),

$$b = W(P^T W)^{-1} g^T \tag{4}$$

where T is the latent matrix and P is calculated using equation (5),

$$P^T = W^T \tilde{X}^T X \tag{5}$$

Where $\tilde{X}$ is the responses and W is the corresponding eigen vector.

The XLSTAT analysis shows that the dependent variable has various levels of correlations with different independent variables. Based on these correlation values, some independent variables are tested to know the sensitivity of the dependent variable to the change in their values.

ANN Modelling

Different ANN configurations and modelling have been investigated by many authors. Often, these configurations or structures are chosen and trained by users till the models outputs are satisfactory. ANN modelling techniques popularly follow the configuration procedure proposed by Jain and Indurthy (2003). For example, Hanspal et al. (2013) simulated two-phase flow systems with ANN. In their work, single-hidden layer and double-hidden layer ANN configurations were tested with different number of neurons. Their results show that both configurations perform efficiently, at different regions of saturation. Also, Abidoye and Das (2015) utilised different ANN configurations with various number of neurons, to predict the influence of dynamic effects on the two-phase flow properties. They found that double-hidden layers perform better than the single-hidden layer. However, these authors noticed that the differences in the predicted values by the different configurations were small. Thus, it was said that a well-trained and validated single-layer ANN structure should suffice (Hanspal et al. 2013).

As a result, in this work, ANN network was created using two-hidden layers with two neurons in each of the layers. This configuration was chosen for simplicity and also to readily obtain satisfactory performance. In line with the conclusion of Hanspal et al. (2013), the ANN structure was trained in several rounds till satisfactory output was obtained with at least R^2 of 0.9. To implement the simulation procedure in MATLAB, program files were prepared with lines of code to create, train, validate and test the network as well as to generate the goodness of fit parameters of the data points using correlation coefficients (R^2) and mean square error

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(MSE). The program divides the dataset randomly into 60, 20 and 20% corresponding to the data for training, validation and testing, respectively.

Curve-fitting function called Levenberg-Marquardt function was used in training the network. The function optimizes the parameter of the model curve in the nonlinear least squares problems. It uses back-propagation algorithm that consists of iterative adjustment of the weights and biases, which were used by the transfer function to relate the input layer to the hidden layer. The training process is terminated when the error between the input and the output reduces below the previously defined minimum. Feed forward type of network was used as it is the commonest network in engineering application. 'Tansig' transfer function was at the two hidden layers. The transfer function calculates a layer's output from its net input. Mean square error (MSE) was used as the network default performance criterion relating the calculated output from the model to the actual target.

In the training process, the epochs and goals serve as the stopping criteria of the number of iterations and the error tolerance, respectively. Epoch is the maximum number of times all of the training sets are presented to the network while goal refers to the maximum error tolerance between the predicted and the actual output. Thus, the training stops if the error goal is satisfactory or the maximum number of epochs is attained. In this work, an epoch of 200 and a goal of zero were used. The network trainings thus stopped when the number of iteration exceeded the stated epochs or if the error tolerance is achieved. At the end of the training, network object is generated with indication of the best validation performance. The result from the training giving the best performance was then selected. Criteria for the analyses of the performances of the network include the coefficient of correlation (R^2) and the mean square error (MSE) while the network with the best performance criteria is saved for use in the prediction of the parameter sensitivity. Mean squared error measures the average of the squares of the errors between the observed value and the predicted or estimated value. The mathematical expressions for the correlation coefficients and mean square error (MSE) are shown in equations (6) and (7), respectively,

$$R^2 = 1 - \frac{\Sigma(Y_{measured} - Y_{predicted})^2}{\Sigma\left(Y_{measured} - \frac{\Sigma Y_{measured}}{N}\right)^2} \tag{6}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_{measured} - Y_{predicted}\right)^2 \tag{7}$$

N = Total number of data points predicted, $Y_{measured}$= observed or target values of energy gain, Ev, and $Y_{predicted}$ = predicted or calculated value of energy gain.

The sensitivity analysis was performed with the best performing network as described above. To do this, the Pearson's correlation coefficient derived from the XLSTAT analysis serves as a good guide. The independent parameters that are well correlated to the output variable are increased by 10 and/or 20%. The network with satisfactory performance saved from ANN was then used to predict the impact of the change in each of these parameters on the output.

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RESULTS AND DISCUSSION

After the preliminary arrangements and sorting of the data, the statistical analysis of the results and the ANN modelling of the targeted output (Ev) were performed. The results from these efforts are presented in this section.

Figure 1 shows the regression analysis of the ANN prediction from the list of independent variables discussed earlier. It can be seen that the round of training adopted in this work yields a very good model network. This is evident in the cluster of the data around the perfect fit line in Figure 1. This is further testified by the high R^2 value of ~1. Thus, the training procedure in this work is very good and reliable. Furthermore, Figure 2 shows the training, validation and testing processes in the ANN modelling. It can be seen from the figure that the network learns gradually. This results in the gradual decrease in the mean square error (MSE) in the figure. This behaviour is similar for the training, validation and testing processes. In fact, the very low MSE value (8.5×10^{-5}) is a further attestation of the network reliable performance.

Figure 3 shows that the ANN predictions match the experimental data well. The experimental data consist of data from all stations for all turbines. The figure proves that ANN can perform efficiently in the prediction of experimental results, if proper training of the network is performed (Hanspal et al. 2013).

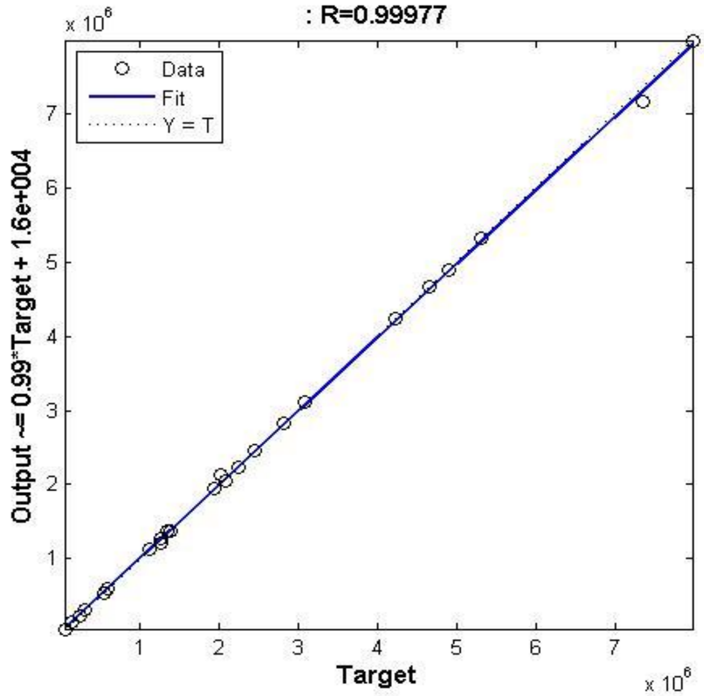

Figure 1: Regression analysis of the ANN prediction of energy gain (target)

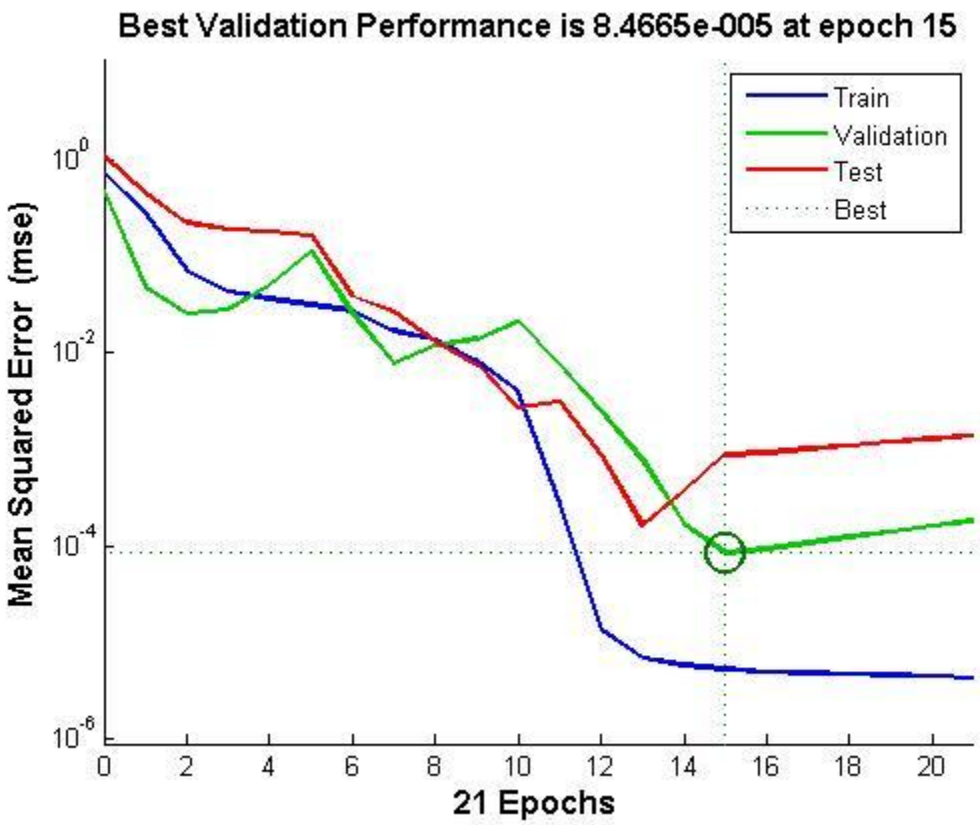

Figure 2: Performances of the ANN prediction of the energy gain during training, validation and testing processes.

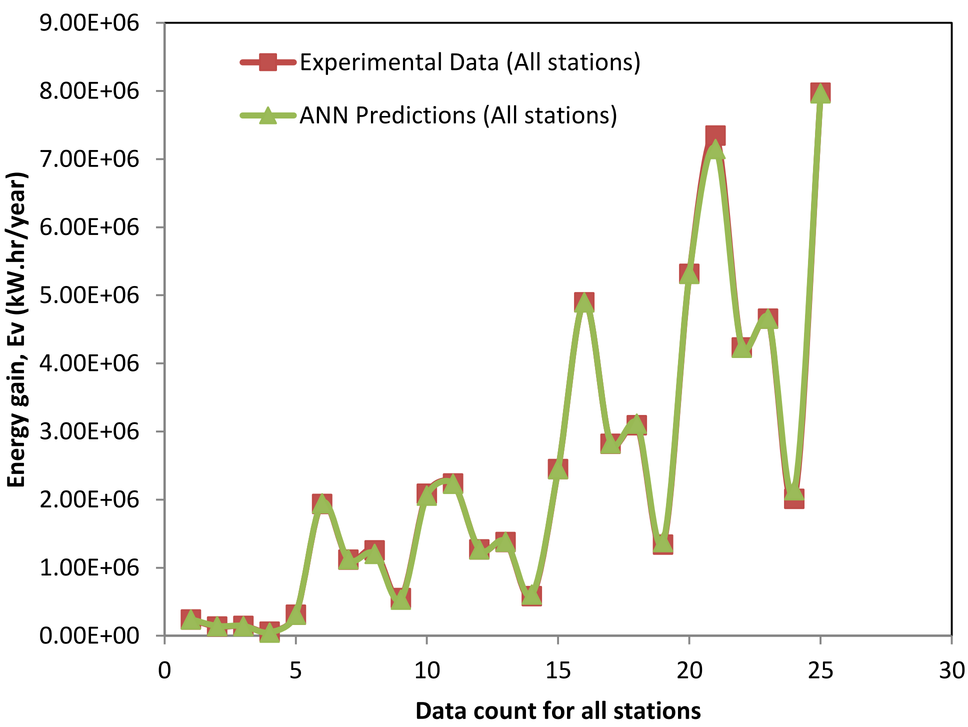

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Figure 3: ANN predcition of experimental data for energy gains from wind turbines at all stations

Following succesful prediction of experimental data, as shown in Figure 3, it is desired to know the sensitivity of the energy gain to the environmental and system parameters, related to the investigations. To do this, the Pearson correlation coefficients were determined. These coefficients for different parameters are shown in Figure 4 for the energy gain. It can be seen in Figure 4 that many parameters are positively and highly correlated with energy gain. Among the highly correlated parameters are the rotor diameter (Rd), Hub height (Hh), Annual mean wind speed (Am), etc. In this work, sensitivity of the energy gain to the few of these selected parameters are examined with the aid of the ANN. It will be recalled that a well-trained network with high R^2 and very low mean square error (MSE) from ANN was saved in MATLAB for reuse in the sensitivity analysis. The sensistivity of the energy gain was examined for 10 and 20% increases in some of these parameters for different turbines.

In Figure 5, ANN shows proficiency in predicting the sensitivity of the energy gain to the 10% increase in the rotor diameter (Rd) for 100 kW turbine at all stations. It can be seen that the energy gain rises above the original value for 10% increase in the Rd. The only exception occurs at the Queen Alia Airport (C), where the energy gain remains unchanged. Reasons for this might include the low value of the original energy gain at the station. There might be a threshold value of energy gain below which a change in the system parameters will exhibit no change or sensitivity in energy output.Reason for this can also inferred from low wind speed of the station. Low wind speed is often instrumental to poor energy gain (Bataineh and Dalalah 2013; Ammari et al. 2014).

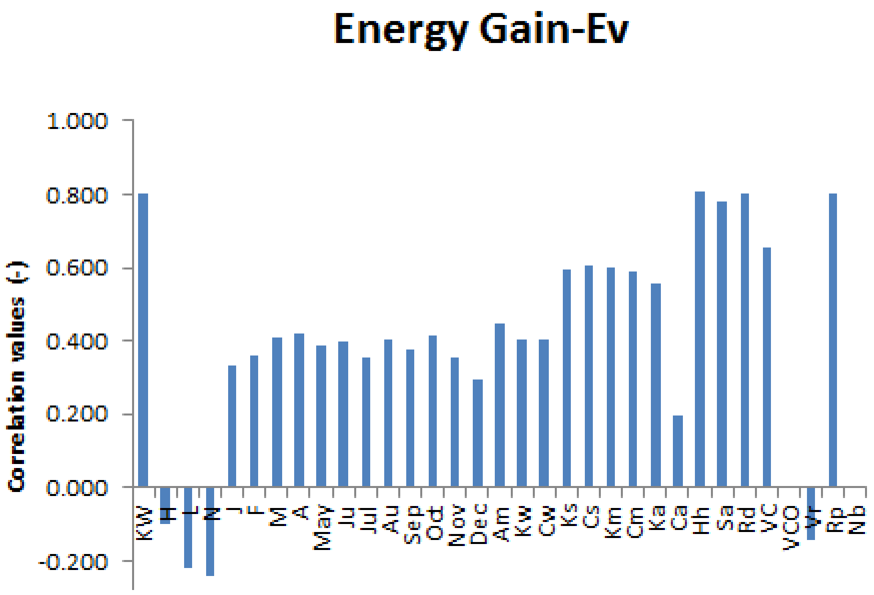

Figure 4: Pearson correlation coefficients for the variables related to energy gains

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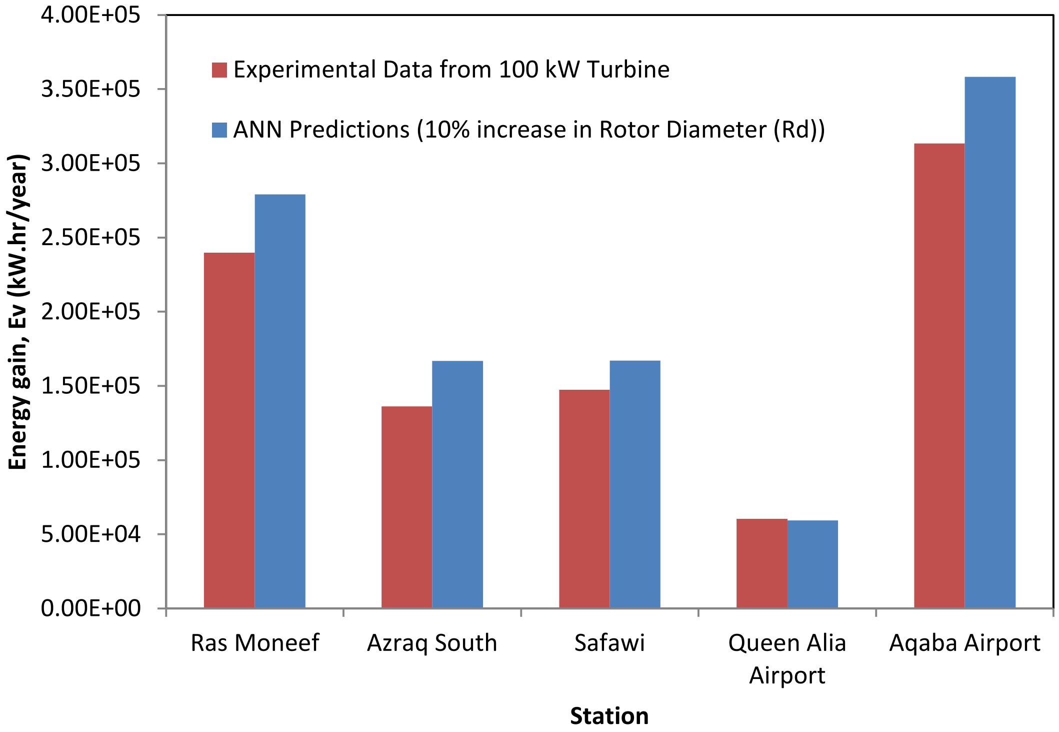

Figure 5: ANN predictions of energy gains based on 10% increase in rotor diameter for 100 kW turbine

This prediction throws more light on the work of Ammari et al. (2014). In their work, the performances of the wind farms at the different geographical locations, are mainly attributed to the environmental factors like wind speeds. Going by the results displayed in Figure 5, it can be said that the system characteristics like turbine's rotor diameter plays a significant role in the energy gains from wind farm. The results imply that the turbine characteristics and environmental factor are jointly influential. For example, the low energy gain at the Queen Alia Airport (C) is partly attributed to the low wind energy potential of this site (Ammari et al. 2014). In fact, the site has the least value of annual mean wind speed of all the sites considered.

Similar behaviour is shown in Figure 6, where the increase in rotor diameter by 10% (for 900 kW turbine) increases the energy gains at all stations. However, unlike the100 kW turbine shown in Figure 5, at Queen Alia Airport, there is also an increase in energy gain as shown in Figure 6, when 900 kW turbine was used. This seems to point out another dimension of the phenomenon of threshold value, discussed earlier. Critical look into the two scenarios (Figures 5 and 6) show that they are different operations with different turbine capacities. Figure 6 involves higher turbine capacity-900kW, while Figure 5 is for 100 kW turbine. Further analysis shows that the earlier hypothesis of threshold energy gain still subsists. For example, in the experimental investigations, the energy gain at the Queen Alia Airport with 100 kW turbine is around $6x10^4$ kW.hr/year, while the energy gain with 900 kW (shown in Figure 6) is $5.8\ x10^5$ kW.hr/year, for the same airport. At least, difference of one order of magnitude exists between these values. The above results imply that with higher turbine capacity, a low-potential site will have higher energy gain and that the site can escape threshold-value effect if the original energy gain exceeds the threshold. As a result, increase in system characteristics like turbine's rotor diameter can increase the energy gain value for such site.

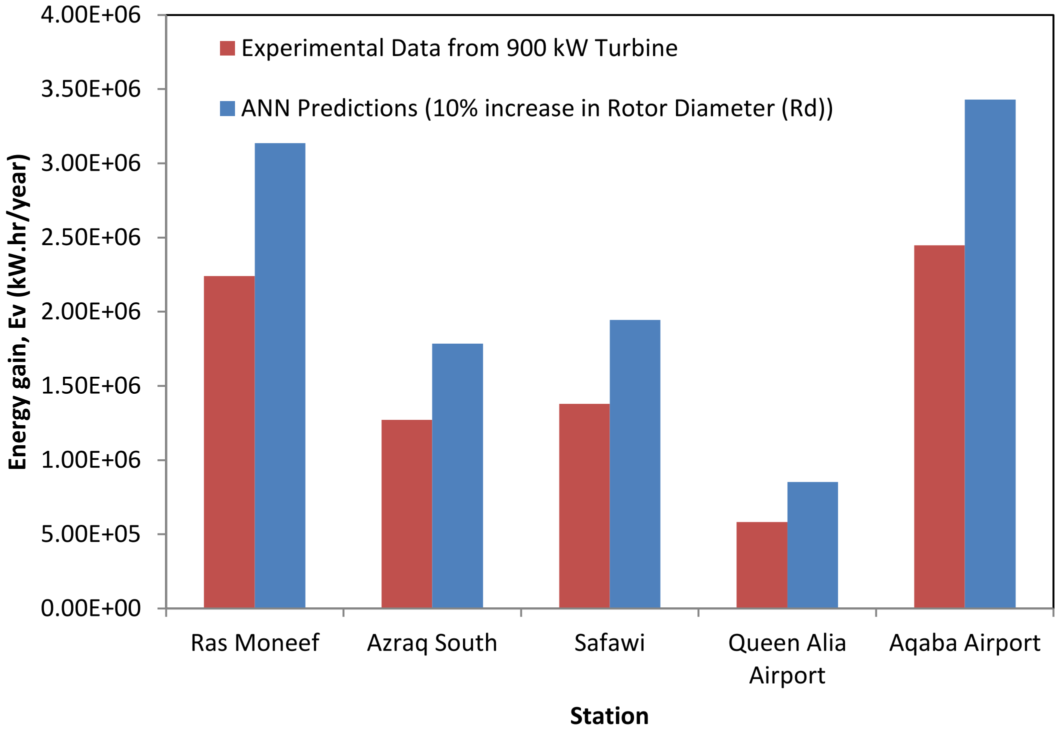

Figure 6: ANN predictions of energy gains based on 10% increase in rotor diameter for 900 kW turbine.

Further prediction of the energy gain is presented in Figure 7 for 3000 kW turbine. Here, the results show direct proportionality of the energy gain to the change in the rotor diameter of the turbine. At 10 and 20% increases in rotor diameter, the energy gain is increased at all stations. It should be noted that at Queen Alia Airport, the energy gain from the experimental results using 3000 kW turbine has clearly exceeded the threshold value that is suggested in the earlier discussion.

Looking further into Figure 4, hub height (Hh) is another parameter that has high correlation value with the energy gain. Figure 8 presents the impacts of the hub height on the energy gain for 3000 kW turbine at all stations. At 10 and 20% increases in hub height, there are considerable increases in the energy gain at all stations.

The above discussions show the importance of system characteristics on the energy gains from wind farm system. In this work, the system characteristics are mainly attributed to the turbines. They have been shown to determine significant performance of a wind farm system. It is reported that the energy output depends on the season's weather, turbine characteristics, location and wind speed (Santos et al. 2015; Capps et al. (2014); Chang et al. 2003; Ammari et al. 2014). This work is elucidating the significant role of the turbine characteristics in the performance of wind farm system, using a cheap and simple computational technique. Interests in these turbine characteristics have been expressed earlier by Capps et al. (2014). They pointed out the significances of turbine characteristics like rotor diameter, hub height and rated power. For each characteristic, they find complex and substantial geographical variations in the sensitivity of energy generation. This further justifies the use of ANN in this work to capture these complex relationships among energy gain, environmental factors and turbine

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characteristics. Specifically, they find that an increase in rotor diameter typically results in wind energy boost. Thus, there is a net increase in energy gain for increase in rotor diameter.

Owing to its cubic relation with power, the wind speed is often considered to be the most important parameter needed to appraise energy output potential of a wind farm. Ammari et al. (2014) shows the range of wind speed data collected on monthly basis for a year period at all stations. It is clear from Figure 4 that for all the wind speed parameters, the annual mean wind speed (Am) has the highest correlation with the energy gain. Therefore, the impact of annual mean wind speed (Am) on the energy gain is investigated. Figure 9 shows the changes in energy gain for the 10 and 20% increases in annual mean wind speed. The figure shows that there is increase in energy gain with the increase in annual mean wind speed. But the change in energy gain is less significant in comparison to the earlier figures. There are only slight changes in energy gain with increases in annual mean speed, as shown in Figure 9. It can be inferred that the characteristics of the turbine affect the energy output more than the environmental factors like wind speed.

The discussions above reveal the relationships between energy generation from wind farm system and the influential environmental factors as well as the turbine characteristics. It is widely known that the dynamics of wind turbine behaviour are complex and critical to the optimization of energy gain in wind farm system (Mckay et al. 2014). It is also challenging to identify factors, causing desired or undesired effects in the system. As a result, this work assembles array of parameters, believed to be instrumental to the optimal performance of the wind farm system. The task of analysing these parameters was assigned to ANN, which possesses the capacity to capture non-linear integrating effect in complex relationships between the dependent and the independent variables. The quantification of the effect that these factors have is valuable for making improvements to both power performance and turbine health (Mckay et al. 2014). The results of the modeling show the relative effects of different factors on the energy generation from wind farm system.

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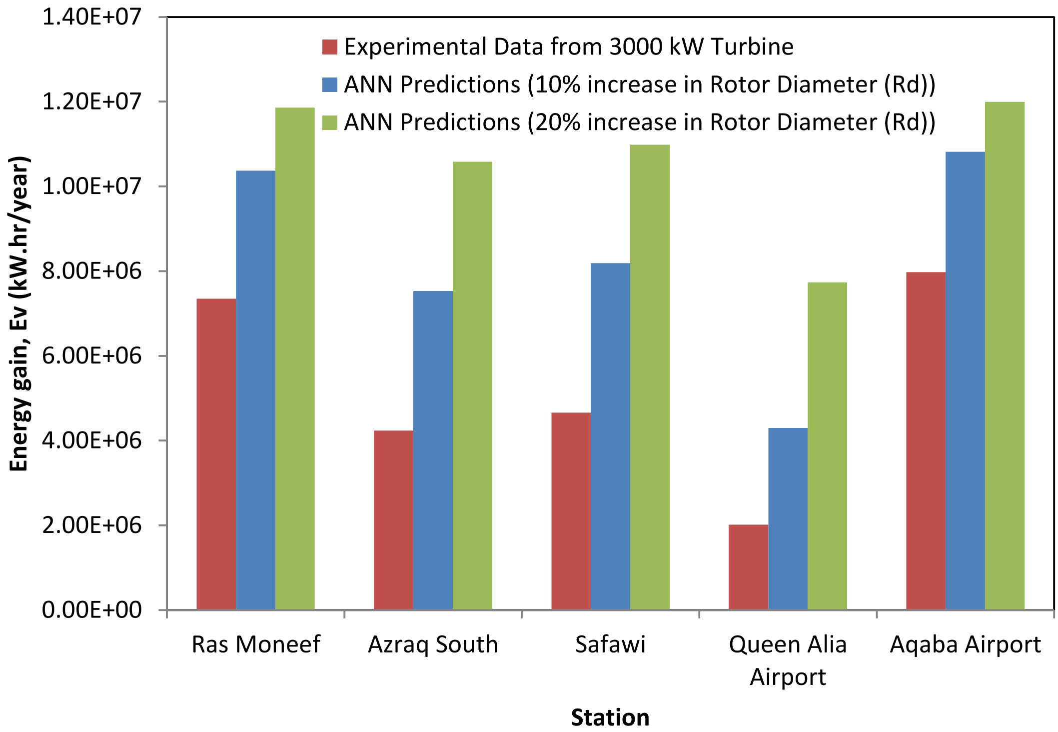

Figure 7: ANN predictions of energy gains based on 10 and 20% increases in rotor diameter for 3000 kW turbine

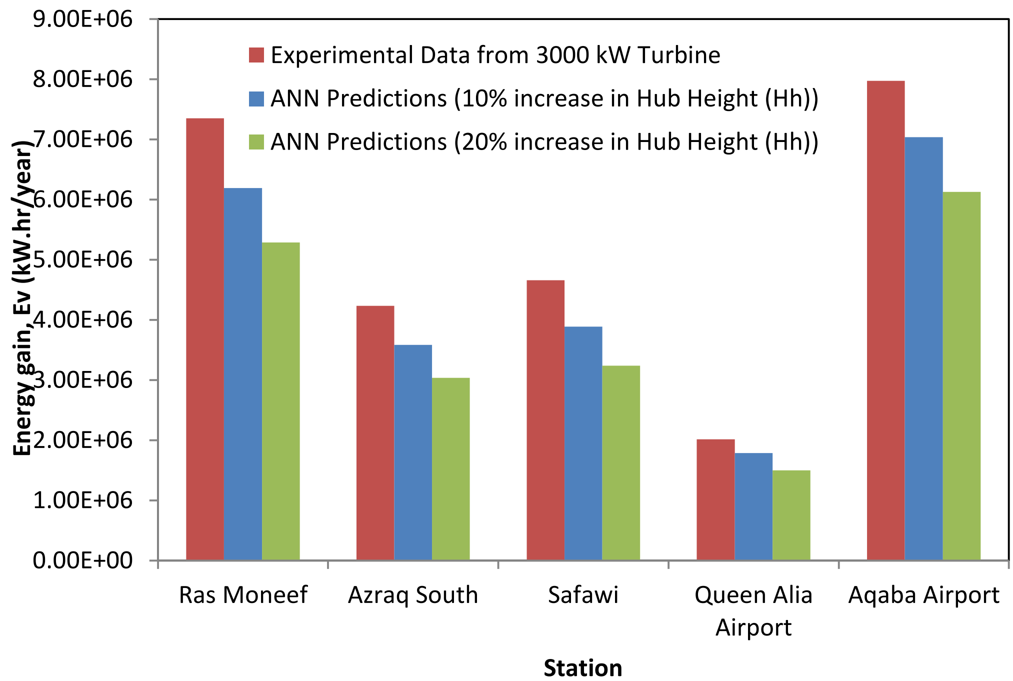

Figure 8: ANN predictions of energy gains based on 10 and 20% increases in hub height for 3000 kW turbine

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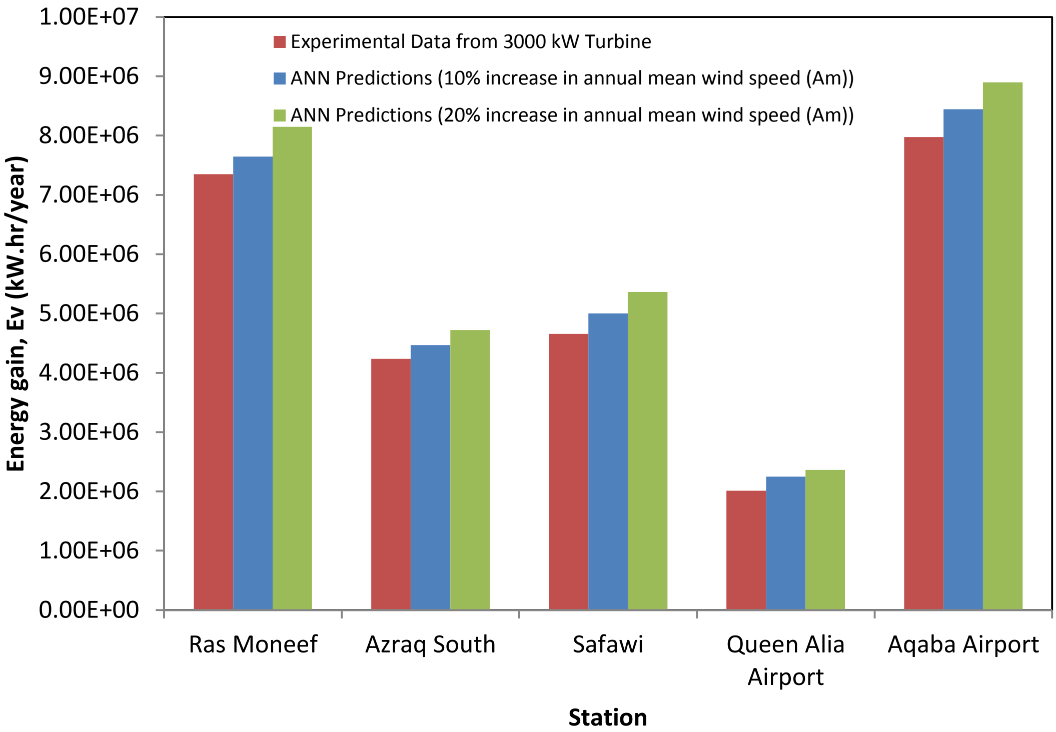

Figure 9: ANN predictions of energy gains based on 10 and 20% increases in annual mean wind speed for 3000 kW turbine

CONCLUSIONS

System and environmental parameters affecting the output parameter of the wind farm system at different stations in Jordan have been computationally investigated, using artificial neural network (ANN). Among the several variables identified, statistical analysis showed the relevance of selected parameters to the different outputs, with the aid of the Pearson's correlation coefficients.

ANN shows proficiency in the prediction of the original experimental data for all the stations and turbines. The energy gain increases with the increase in the system and environmental parameters, with more significant increase recorded in the turbine parameters like rotor diameter and hub height. Findings show that the turbine characteristics have more significant impact on the energy gain than the environmental factor like wind speed.

However, there appears to be phenomena of threshold values in the output parameter, which determine the impact of change in the input parameters on the eventual responses of the output. It can be deduced that there is a minimum energy gain value below which increase in the system/environmental parameters will not have positive impact on the energy output.

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REFERENCES

Abidoye, L.K. and Das D.B. (2015). Artificial neural network modeling of scale-dependent dynamic capillary pressure effects in two-phase flow in porous media. Journal of Hydroinformatics, 17(3), pp. 446-461.

Abidoye, L.K. and Mahdi, F.M. (2014). Novel linear and nonlinear equations for the higher heating values of municipal solid wastes and the implications of carbon to energy ratios. Journal of Energy Technologies and Policy, 4(5), pp. 14-27.

Acker, T. L., Williams, S. K., Duque, E. P. N., Brummels, G., and Buechler, J. (2007). Windresource assessment in the state of Arizona: Inventory, capacity factor, and cost.Renewable Energy, 32, 1453–1466.

Amato, F., López, A., Peña-Méndez, E.M., Vaňhara, P., Hampl, A., Havel, J. (2013). Artificial neural networks in medical diagnosis. Journal of Applied Biomedicine, 11(2), pp.47–58.

Ammari, H. D., Al-Rwashdeh, S. S., Al-Najideen, M. I. (2014). Evaluation of wind energy potential and electricity generation at five locations in Jordan. Sustainable Cities and Society, Volume 15, pp. 135–143.

American Wind Energy Association (AWEA), www.awea.org

Bataineh, K.M., and Dalalah, D. (2013). Assessment of wind energy potential for selected areas in Jordan. Renewable Energy, 59, pp. 75-81.

Capps, S-B, Hall, A., Hughes, M. (2014). Sensitivity of southern California wind energy to turbine characteristics. 17(1), pp.141-159.

Chang, T-J, Wu, Y-T, Hsu, H-Y, Chu, C-R, Liao, C-M (2003). Assessment of wind characteristics and wind turbine characteristics in Taiwan. Renewable Energy, 28(6), pp. 851-871.

Hanspal, N.S., Allison B.A., Deka L., Das D.B. (2013). Artificial neural network (ANN) modeling of dynamic effects on two-phase flow in homogenous porous media. Journal of Hydroinformatics, 15(2), pp. 540-554.

Jain, A. and Indurthy, P. (2003). Comparative analysis of event-based rainfall-runoff modelling techniques – deterministic, statistical and artificial neural networks. Journal of Hydrological Engineering 9 (6), 1084–0699.

Kalogirou, S.A. (1999). Applications of artificial neural-networks for. Energy Systems. Applied Energy, 40(10), pp. 17-35.

Khashei, M. and Bijari, M. (2014). Fuzzy artificial neural network (p, d, q) model for incomplete financial time series forecasting. Journal of Intelligent and Fuzzy Systems 26(2), pp. 831-845.

Khudaida K.J. and Das D.B. (2014). A numerical study of capillary pressure–saturation relationship for supercritical carbon dioxide (CO_2) injection in deep saline aquifer. Chem Eng Res Des, 92(12), pp. 3017–3030.

McKay, P.M., Carriveau, R., Ting, D. S-K, Johrendt, J.L. (2014). Global sensitivity analysis of wind turbine power output. Wind Energy, 17(7), pp. 983-995.

Mueller, A. V. and Hemond, H.F. (2013). Extended artificial neural networks: Incorporation of a priori chemical knowledge enables use of ion selective electrodes for in-situ measurement of ions at environmentally relevant levels. Talanta, 117, pp.112–118. DOI: 10.1016/j.talanta.2013.08.045

McKendry, P. (2002). Energy production from biomass (part 1): overview of biomass, Bioresour. Technol. 83, 37–46.

Lurque, R., Davilla, L.H., Campelo, J.M., Clark, J.H., Hidalgo, J.M., Luna, D. (2008). Biofuels: a technological perspective, Energy Environ. Sci. 1–5, 542–564.

ISSN 2055-0197(Print), ISSN 2055-0200(Online)

Rehman, S., El-Amin, I. M., Ahmad, F., Shaahid, S. M., Al-Shehri, A. M., and Bakhashwain,J. M. (2007). Wind power resource assessment for Rafha, Saudi Arabia. Renewableand Sustainable Energy Reviews, 11, 937–950.

Santos, J.A., Rochinha, C., Liberato, M.L.R., Reyers, M., Pinto, J.G. (2015). Projected changes in wind energy potentials over Iberia. Renewable Energy. 75, pp. 68-80.

Schumann, S., Nolte, L.-P. and Zheng, G. (2013). Comparison of partial least squares regression and principal component regression for pelvic shape prediction. Journal of biomechanics, 46(1), pp.197–199.

Spalding, D.B. (1981). A general purpose computer program for multi-dimensional one-and two-phase flow. Mathematics and Computers in Simulation, 23(3), pp.267–276.

The World Energy Council (WEC), www.worldenergy.org

Wang, L. and Fu, K. (2008). Artificial neural networks, Wiley Online Library

Yurdakul, M. and Akdas, H. (2013). Modeling uniaxial compressive strength of building stones using non-destructive test results as neural networks input parameters. Construction and Building Materials, 47, pp.1010–1019.

Zhang, G., Eddy Patuwo, B. and Y. Hu, M. (1998). Forecasting with artificial neural networks: International Journal of Forecasting, 14(1), pp.35–62.

ISSN 2055-0197(Print), ISSN 2055-0200(Online)