Energy Prediction of the optimized parameters of Commercial greenhouse in Middle East climatic condition using Artificial Neural Network.

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Abstract

Dynamic modeling is the most feasible platform to study agronomical precision level details. Optimized uncertain parameters using Particle swarm optimization (PSO) and Genetic algorithm (GA) to be further interpreted using Artificial Neural Network technique using time series configurations- Nonlinear Auto Regressive with exogenous inputs (NARX) for a an energy prediction for a forecasted period for the upgraded commercial greenhouse.

Keywords: Greenhouse HVAC, Covering material, Greenhouse climate control, Optimization , Energy prediction.

1.Introduction

Dynamic modeling of the greenhouse climate is generally used for the optimization of the uncertain parameters using various dynamic equations directly related to the greenhouse indoor climate. Greenhouse operational cost in terms of commercial energy spent is the major milestone in terms of yield management. In some cases, due to the anti-seasonal nature of the greenhouse operations, energy consumption cost may reach almost 50% of the operational cost of commercial greenhouses. Therefore, it is important to predict the energy consumptions in the greenhouses. Parameter optimization-based algorithms based on energy conservation principle can provide a stronger platform in developing energy-based greenhouse optimization models (Yongato Shen et al., (2018)) [1]. In order to utilize the energy prediction in an efficient approach, the growers can implement intelligent system (Korner et al., (2008)) [2].

Artificial neural network (ANN) is one of the effective methods to do the same. In the early ages of the greenhouse technology, some ANN models developed using simple logics to predict the peak energy spent and consumption. Progressively, the ANN models used for the load prediction and cascade models for hourly prediction. All the above discussed models revealed the importance of existing temperature as an input variable to predict the future temperature for the energy balance.

In the present study, the uncertain parameters for the upgraded greenhouse model for energy consumption are optimized using particle swarm optimization and genetic algorithm. Furthermore, an electrical energy consumption prediction using ANN is also carried out using time series configurations-Nonlinear Auto Regressive with exogenous inputs (NARX).

2.Artificial Neural Network (ANN)

ANN is being used to solve the complex models. Among the available methods of artificial neural networks, the NARX, a dynamic recurrent method, is used to solve the time series problem (Bhaskar et al., (2012) [3] and (Liu et al., (2010)) [4]. In the present study, NARX based ANN model has been used for electrical energy consumption using different sensor readings logged in the greenhouse which can be used for forecasting the energy consumption. For the current model, input variables are outside wind speed, outside temperature, outside relative humidity and solar radiation which were recorded in the greenhouse climate control module. Predictor is designed in such a way that the same can provide the energy prediction in KW $h^{-1}$and the same has been designed to forecast the values using the data collected for the peak summer time of July month as well as the data for the whole year. Schematic of the current set of variables used as inputs and outputs are shown in Figure 1. The nonlinear autoregressive network with exogenous inputs (NARX) is a recurrent dynamic network, with feedback connections enclosing several layers of the network. The NARX model is based on the linear ARX model, which is commonly used in time-series modeling (Wen et al., (2013) [5]. The equation defining NARX model is

$$y(t) = f\big(y(t-1)\big), y(t-2), \dots\dots, y(t-ny), u(t-1), u(t-2), \dots., u(t-nu)) \quad (1)$$

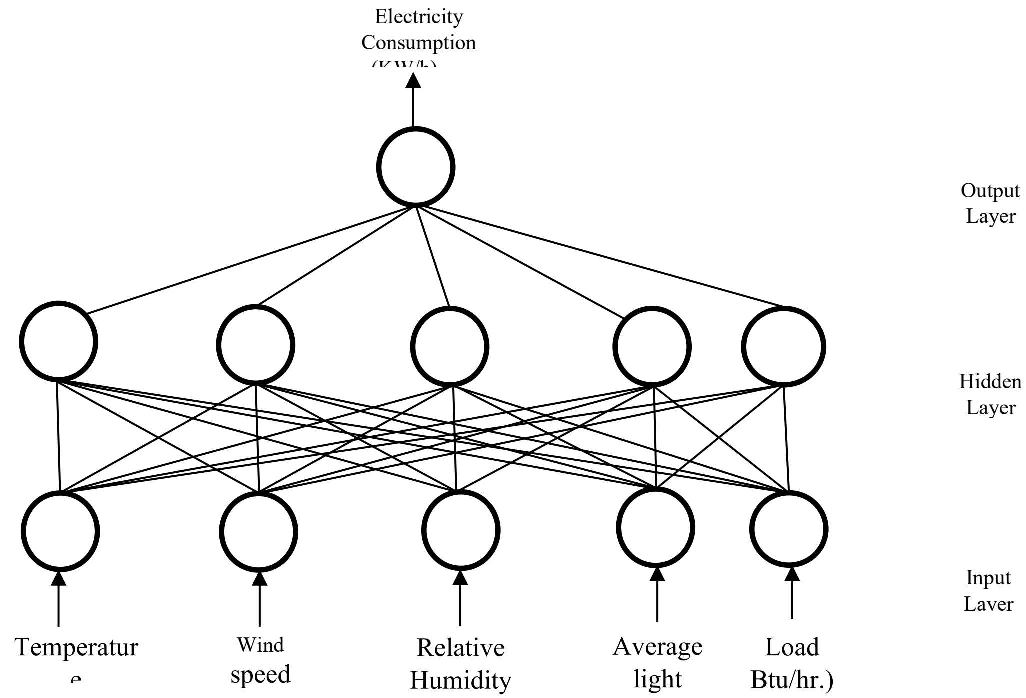

Figure 1 : Feed Forward Network of an ANN

3.Nonlinear Auto Regressive with Exogenous Inputs (NARX)

Where the dependent next value output signal y(t) is regressed on previous values of the y(t) signal and an independent (exogenous) input signal is the previous values.

3.1. Series Parallel Architecture

Because the true output is available during the training of the network, one could create a series –parallel architecture, in which the true output is used instead of feeding back the estimated output. This has two advantages: the first is that the input to the feed forward network is more accurate and the second is that the resulting network has a purely feed forward architecture, and static back propagation can be used for training.

3.2.Parallel Architecture

Later this architecture is converted into parallel architecture for the prediction. The prediction of the next value depends on the inputs and previous outputs to the network. The dependence on the previous output can be adjusted by using delays, input delays and feedback delays. Block diagram of the detailed Matlab steps for the training in ANN has shown below in Figure 2.

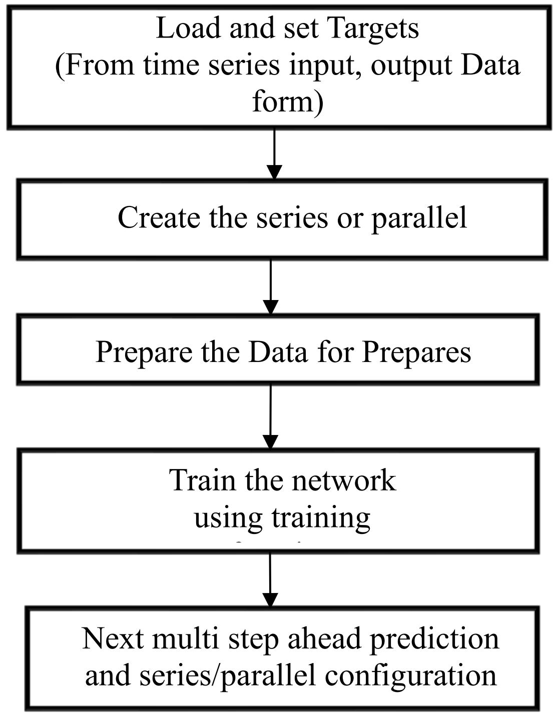

Figure 2 : Flow chart of NARX training in MATLAB

3.3.Correlation between sensor inputs and Energy consumption

Correlation coefficient and 'P' values were calculated to check the correlation between the inputs and output for the energy consumption prediction. In the present study, the variables are defined as follows: X1 is the Outdoor average temperature in ^{o}C, X2 is the Outdoor Average relative humidity in %, X3 is the average wind speed in m/s, X4 as outdoor Average light ($W.m^{-2}$) and X5 as air-conditioning load in Btu/hr. Above details has been comprehended in the Table 1.

Table 1 : Correlation coefficient for each variable.

Variable	Correlation Coefficient	P value
X1	0.0646	0.0783
X2	-0.0837	0.0225
X3	0.0516	0.1593
X4	-0.0432	0.239
X5	0.2612	4.54e-13

The Pearson correlation coefficient was estimated for the different variables for the output using the Equation 2. The significance of correlation coefficients is evaluated using p value based on t distribution.

The p-value is 2 × P (T > t) where T follows a t distribution with n – 2 degrees of freedom, where 'r' is the correlation coefficient and 'n' is the number of observations.

$$r = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \tag{2}$$

$$\mathrm{t} = \frac{\mathrm{r}\sqrt{\mathrm{n}-2}}{1-\mathrm{r}\hat{}2} \tag{3}$$

3.4. Methodology for NARX net in MATLAB

1. Import the data stored in xls file into matlab and prepare the data suitable for analysis which involves the conversion of double to cell. The data set is divided into training, testing and validation in the ratio of 70:15:15. The data used for the proposed network is given below in Table 2.

2. Design of network with one input layer with 5 inputs, one output layer and a hidden layer with delay as shown below in Figure 3.

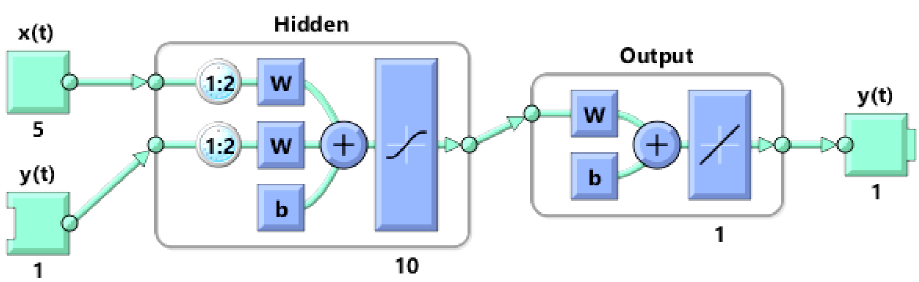

Figure 3: Proposed Energy Prediction ANN Cascaded Model-open Loop

Table 2. : Average Consumption data of HVAC Units for the one-month Period

Date (dd-mm-yy)	Outdoor Average relative humidity in %	Outdoor average temperature in °C	Wind speed in m/s	Outdoor Average light ($W.m^{-2}$)	Energy consumption in KWh/m2
01/07/2024	40.65	35.40	35.40	196.22	0.226059
02/07/2024	47.46	34.70	34.70	329.50	0.225366
03/07/2024	59.97	34.67	34.67	316.14	0.231760
04/07/2024	52.27	33.44	33.44	315.95	0.232736
05/07/2024	42.92	34.40	34.40	320.26	0.234146
06/07/2024	44.25	37.11	37.11	275.23	0.230927
07/07/2024	44.38	36.48	36.48	307.05	0.232511
08/07/2024	44.38	36.48	36.48	307.05	0.232511
09/07/2024	44.25	37.11	37.11	275.23	0.230927
10/07/2024	35.83	37.17	37.17	278.68	0.228474
11/07/2024	37.17	36.46	36.46	251.80	0.234777
12/07/2024	35.91	37.55	37.55	259.59	0.236352
13/07/2024	34.61	37.89	37.89	260.28	0.239504
14/07/2024	40.54	36.62	36.62	268.57	0.233963
15/07/2024	40.22	37.59	37.59	272.23	0.235492
16/07/2024	33.76	37.84	37.84	264.97	0.237021
17/07/2024	37.18	36.53	36.53	282.43	0.234159
18/07/2024	36.11	36.40	36.40	258.94	0.242193
19/07/2024	28.56	37.78	37.78	292.45	0.243282
20/07/2024	21.15	36.93	36.93	293.52	0.241762
21/07/2024	31.58	36.66	36.66	281.43	0.244803
22/07/2024	34.23	36.50	36.50	283.26	0.240241
23/07/2024	37.18	36.53	36.53	282.43	0.234159
24/07/2024	36.95	36.59	36.59	273.46	0.231118
25/07/2024	38.62	37.85	37.85	273.56	0.225036
26/07/2024	41.00	37.30	37.30	278.64	0.231118
27/07/2024	36.97	38.35	38.35	289.07	0.225036
28/07/2024	45.17	37.83	37.83	269.06	0.225036
29/07/2024	49.07	36.65	36.65	270.31	0.228077
30/07/2024	51.18	35.11	35.11	296.73	0.225036
31/07/2024	48.37	36.65	36.65	277.67	0.226557

3. The network was trained using the dataset with Max. Epochs=1000, Performance goal =1e-9 mu = 1e+10 and Gradient = 1e-7 and Levenberg-Marquardt training algorithm input delays = 1:2, feedback delays = 1:2 and hidden layer size = 10. The network was trained and the regression plots for training, testing and validation are shown below.

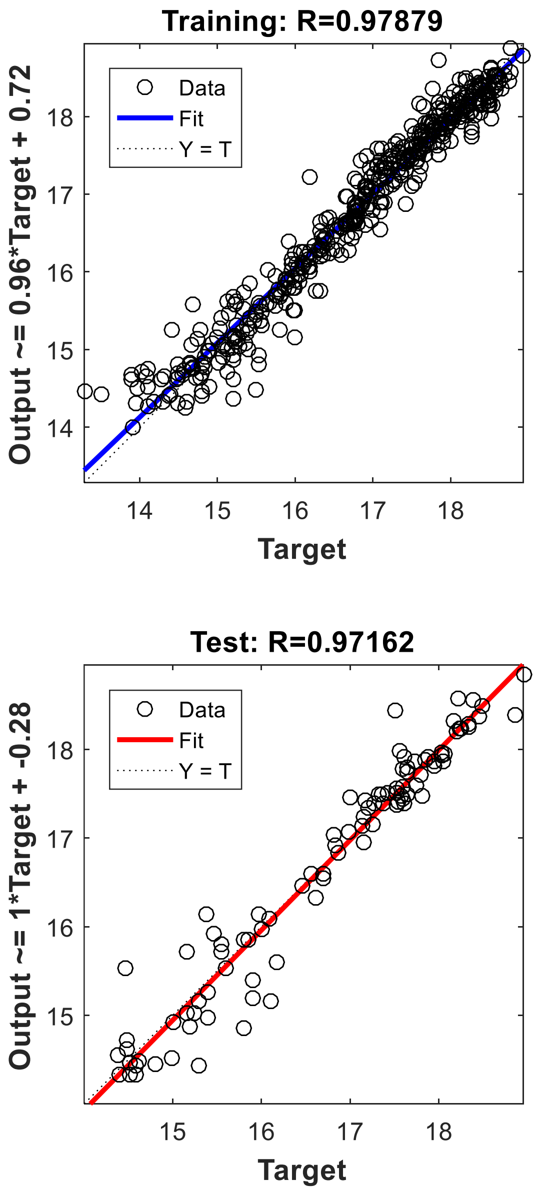

Figure 4. : Proposed energy prediction ANN output in training and validation

A comparison between predicted and actual outputs along with error are given below in figure 5.

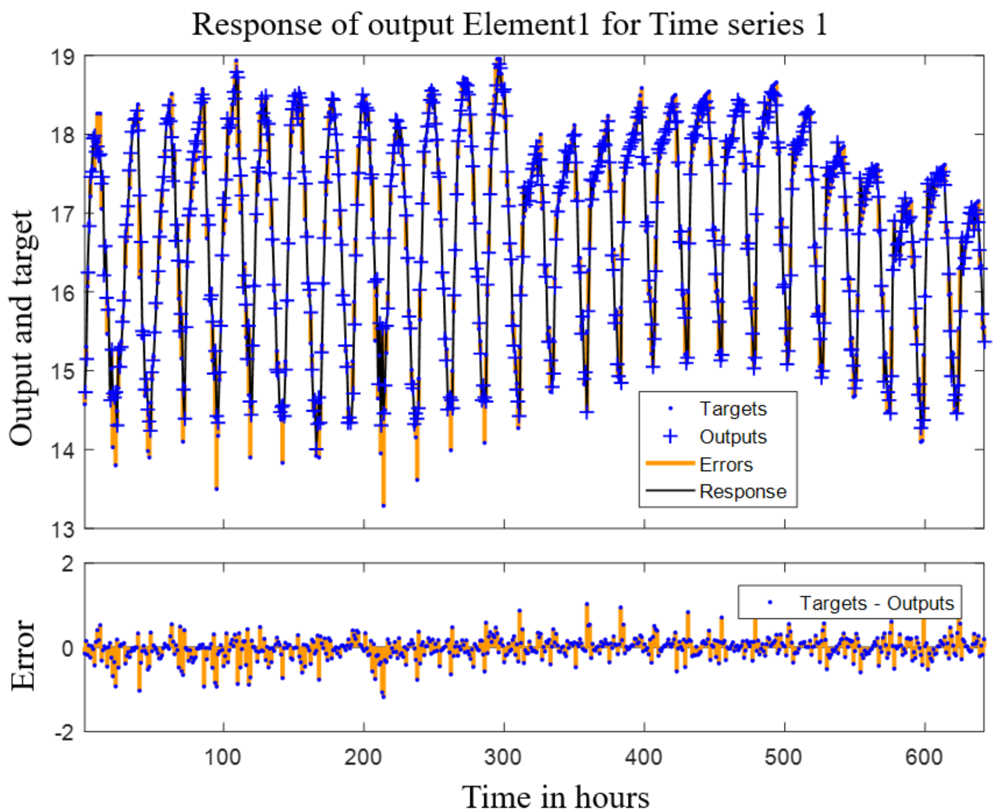

Figure 5: Proposed Energy Prediction ANN model with Error Details

4. The network can be used for prediction by closing the network as shown below. The function closed loop replaces the feedback input with a direct connection from the output layer. The closed loop network can be used for multistep prediction if the inputs are known and proposed cascaded model has shown in Figure 6. Energy prediction using closed loop has shown in Figure 7.

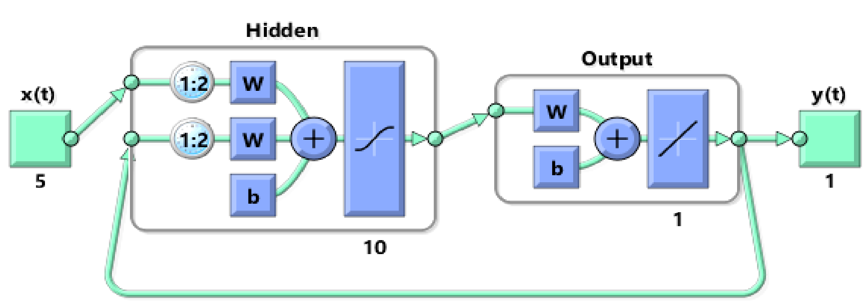

Figure 6 : Proposed Energy Prediction ANN Cascaded Model-closed Loop

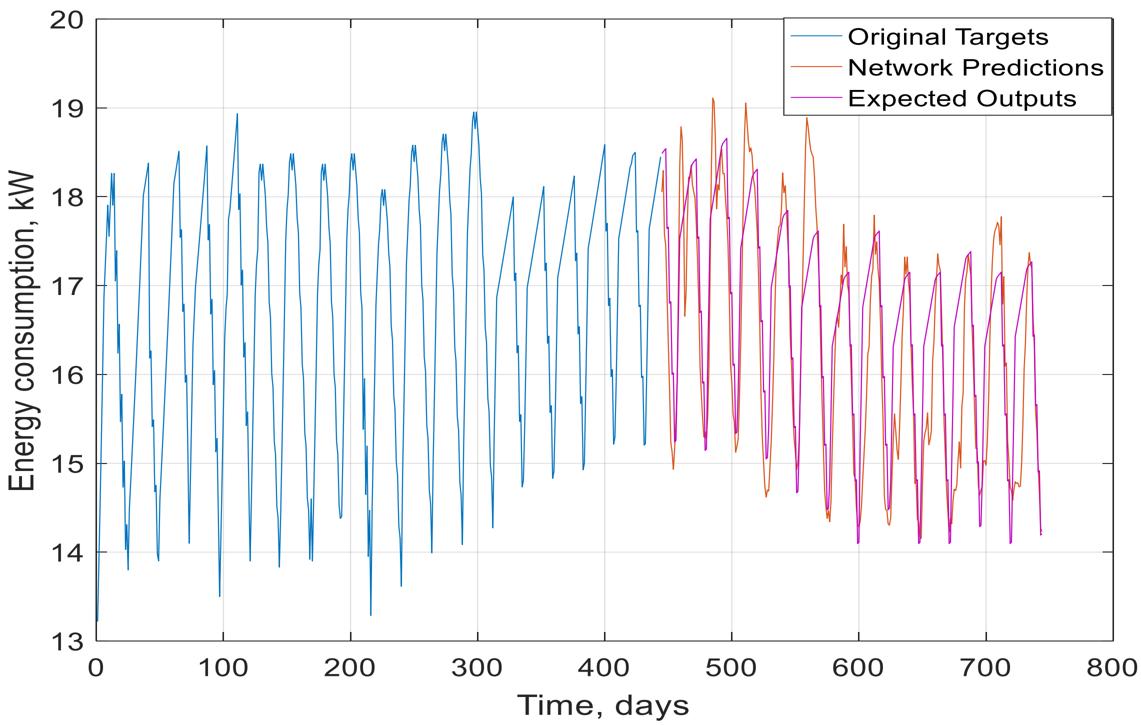

Figure 7 : Energy Prediction Using Closed Loop

5. Step-Ahead Prediction Network for some applications it helps to get the prediction a time step early. The original network returns predicted y(t+1) at the same time it is given y (t+1). For some applications such as decision making, it would help to have predicted y (t+1) once y(t) is available, but before the actual y(t+1) occurs. The network can be made to return its output a timestep early by removing one delay so that its minimal tap delay is now 0 instead of 1. Proposed one step ahead prediction model has shown in Figure 8. The new network returns the same outputs as the original network, but outputs are shifted left one-time step. A step ahead energy prediction carried out has been shown in Figure 9.

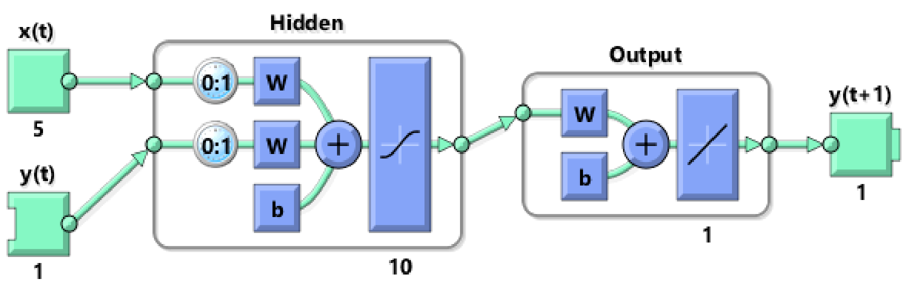

Figure 8. Proposed Energy Prediction ANN Cascaded Model-One Step Ahead Prediction

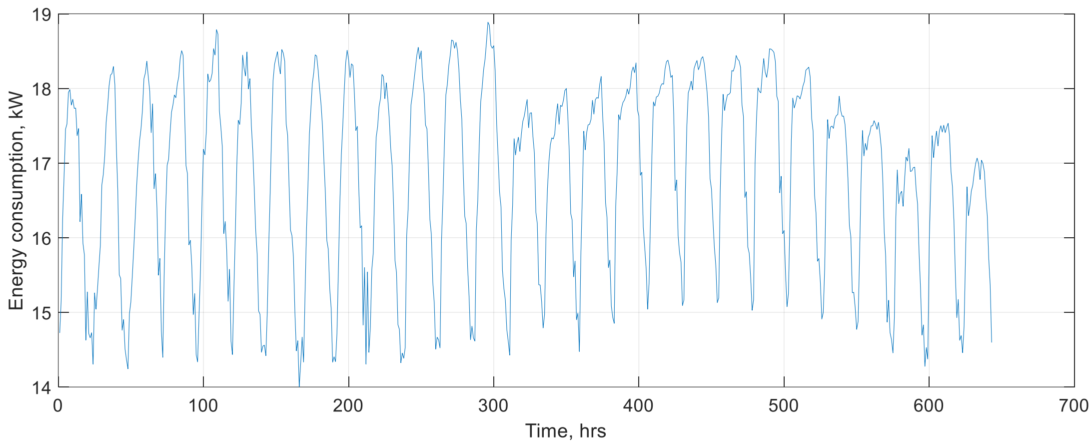

Figure 9 : One Step Ahead Energy Prediction Using NARX

In the present study, NARX model developed various interconnections between the various variables and carried out the prediction five variables were involved in the model as input and correlation coefficient of each variables has been calculated to interpret the error in the model. NARX is time series model for a step ahead prediction with reasonable parameter count and cost (Amrit et al., (2007)) [6], (Hong et al., (2008)) [7]. Model construction in this approach is based on the input output data with a flexible and practicable approach even with a limited information about the system (Barbosa et al., (2011)) [8], (Yassin et al., (2014)) [9]. In the present study we have obtained the energy prediction and step ahead prediction effectively. Data in the year 2024 has been used for the current model. Data set for the month of July 2024 used for evaluating the accuracy. Model evaluation results presented in the Figure 7 for energy prediction and a step ahead prediction has shown in Figure 9.Figure 4 denotes the regression plots between the target and output between training, testing and total regression. Data points indicates the relation between the output and target. Dashed line denotes the reference line and the solid line indicates the best fit between the output and R value represents relationship between the output and targets.

4. Performance of ANN

After training, the neural network is ready for the prediction. The predicted output is compared to the calculated energy consumption and the performance is monitored by calculating the errors by various means of error calculations.

a. Mean Error (ME): It is the basic type of error calculation. it is the average of the errors

$$ME = \frac{1}{N}\sum_{i=1}^{N} Ti - Pi \quad (4)$$

b. Mean Square Error (MSE): It is one of the basic types of error calculation. It is the average of the squares of the errors.

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (Ti - Pi)^2 \quad (5)$$

c. Root Mean Square Error (RMSE): RMSE is the standard deviation of the differences between predicted values and actual values. It is the square root of the average of squares of the errors.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} \ (Ti - Pi)^2} \quad (6)$$

Table 3 : Mean Square Error for Different Architectures

Network architecture	NARX
Open loop	6.6012e-05
Closed loop Multistep prediction	6.0213e-04
Step ahead network	6.6012e-05

Nonlinear autoregressive model (NAR) is an ANN approach to solve time series problems which are in nonlinear nature (Jursa, (2007)) [10], (Mohanty et al., (2015)) [11]. NAR models used previously for the prediction of energy usage in the institutional buildings (Deb et al., (2016)) [12] Performance function used in NAR is the sum of squares of the difference between the actual and predicted (Tyler et al., (2020) [13]. Learning rule for the NAR is based on Levenberg-Marquardt backpropagation procedure (LMBP) (Alwakeel et al., (2010)) [14], Hagan et al., (1994)) [15]. This is the fastest approach to back propagate the second order derivatives. Table 3 shows the mean square error for the architectures of NARX networks used for the study. The error for closed loop is higher than the open loop and step ahead architectures which is a common phenomenon since the closed network makes prediction without reference and untrained data.

6.Conclusion

In the present study, the greenhouse located in Middle East climate was taken as an example to predict the energy for real scenario using two major optimization algorithms. Based on the optimized seven parameters obtained, energy consumption prediction carried out in between 1st July 2025 to 7th July 2025for 7 days cycle in a summer period in United Arab Emirates. Predicted energy trend followed the same modularity as of actual energy consumption but with an optimized result. Exclusively in the present study an energy prediction model has been established in line with the real time energy production for a period of time using the PSO and GA. . Based on the detailed analysis major parameters involved in the energy prediction has been identified. Measured data of the greenhouse environment and states information of the devices are input into the model. Using two major algorithms values of the uncertain parameters optimized. Real data recorded during the experiment cycle of 7 days used to verify the energy prediction. Furthermore, the NARX architectures of neural network modeling were used for electrical energy consumption. The NARX models can be used for predicting the energy consumption using the exogeneous inputs. A further simulation using Non-linear autoregressive neural network (NAR) is to be carried out as future works to interpret the error correctly for the energy prediction. In NAR, the simulation is based on the historical the forecasting is purely depending on the same, furthermore a major challenge is the delays in retrieving the historical data for the model processing.

References

1. Yongtao Shen ID, Ruihua Wei and Lihong Xu Energy Consumption Prediction of a Greenhouse and Optimization of Daily Average Temperature,Energies, 11, 65; doi: 10. 3390/en11010065 (2018).
2. Korner, G. and V. Straten, Decision support for dynamic greenhouse climate control strategies. Computers Electronics Agric., 60: 18–30 (2008).
3. Bhaskar K, Singh SN. AWNN-Assisted Wind Power Forecasting Using Feed-Forward Neural Network. IEEE Transactions on Sustainable Energy; 3: 306-315 (2012).
4. H Liu, HQ Tian, C Chen, Y Li. A hybrid statistical method to predict wind speed and wind power. Renewable Energy.; 35: 1857-1861 (2010).
5. Wen-Yeau Chang. Short-Term Wind Power Forecasting Using the Enhanced Particle Swarm Optimization Based Hybrid Metho. Energies; 6: 4879-4896 (2013).
6. R. Amrit, P. Saha, Stochastic identification of bioreactor process exhibiting in- put multiplicity, Bioprocess Biosyst. Eng. 30 165–172 (2007).
7. Hong, R.J. Mitchell, S. Chen, C.J. Harris, K. Li, and G.W. Irwin, "Model selection approaches for non-linear system identification: a review," vol. 39, pp. 925–946, (2008).
8. B.H.G. Barbosa, L.A. Aguirre, C.B. Martinez, A.P. Braga, Black and gray-box iden- tification of a hydraulic pumping system, IEEE Trans. Control Syst. Technol. 19 398–406 ((2011).
9. A.I.M. Yassin, "Nonlinear auto-regressive model structure selection using bi- nary particle swarm optimization algorithm," (2014).
10. Jursa R Wind power prediction with different artificial intelligence models. In: Proceedings of the European wind energy conference (EWEC), Milan, 2007. Available at: http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.174.8568 (2007).
11. Mohanty S, Patra PK and Sahoo SS Prediction of global solar radiation using nonlinear auto regressive network with exogenous inputs (NARX). In: Proceedings of 39th national systems conference (NSC), Noida, India, 14–16 December (2015).
12. Deb, C.Forecasting diurnal cooling energy load for institutional buildings using Artificial Neural Networks.Energy Build, 121, 284–297 (2016).
13. Tyler Blanchard and Biswanath Samanta, Wind speed forecasting using neural networks, Wind Engineering, Vol. 44(1) 33–48,doi: 10.1177/0309524X19849846 (2020).
14. Alwakeel, M.; Shaaban, Z. Face Recognition based on haar wavelet transform and principal componentanalysis via Levenberg-Marquardt backpropagation neural network. Eur. J. Sci. Res., 42, 25–31 (2010).
15. Hagan, M.T.; Menhaj, M.B. Training feed forward networks with the Marquardt algorithm. IEEE Trans.Neural Netw., 5, 989–993 (1994).