Wind Turbine Class detection Using ANN

Dr. Vikas Pareek, Ms. Shubhi Lall Agarwal

Abstract— Neural computation in expert system is a novel way to eradicate the drawbacks of current expert system technology. The current expert system use rigorous if then else programming and rule based programming logics. If the neuron is designed at an early phase to weed out various rule conditions in an expert system, the capability of the system increases manifold.

This paper uses neural networks to implement AI based expert system. Our approach uses memory based learning mechanism in ANN technique and apply the same in devising the conditions based rules of the expert system. The system is an integration of ANN technique and KBES.

The research paper uses the roughness length, data of IEC wind class and turbine details from 3 companies as input and diagnoses the turbine suitable for a location/site. The paper eventually devises a prototype for the diagnosis of a turbine for a location.

Index Terms— Artificial neural Network, expert system, memory based learning

I. INTRODUCTION

Energy is needed for socio - economic development of any society. Price of petrol and diesel is increasing at an alarming rate. Use of fossil fuels is expected to increase the economic development process of the world population during the next two decades. Hence, there is a grave need to diagnose ways, tools and techniques to develop powerful wind turbine power plants in India.

Yet another reason to promote windmills is to reduce carbon footprints from the environment. Carbon monoxide (CO) is a dangerous gas which is impossible to see, taste and smell. It can kill a person very easily. [1]

II. EXPERT SYSTEM

Expert systems are AI based system that extracts the knowledge of a specialist through interviews and discussions with him for a specific problem domain and write that into a program code. This code can be linked with other such codes in different modules and used for answering questions submitted through a computer.

Normally, an expert systems is made up of 3 parts; a knowledge base, an Inference engine and an Interface.

A. Knowledge-base

Knowledge-based systems have data needs that are reverse of these database requirements. An expert system needs structured data. Object model is the ideal way of representation of data for a knowledge-base.

B. The Inference engine

The inference engine is the program that finds the suitable knowledge in the knowledge base, and infers new knowledge by using rules and logic to infer new facts.

C. The User Interface

The user interface is a means of exchange of messages between a user and the expert systems. It should accept the queries from users and convert them into working commands for the expert system. Proper time should be given to the screen design to make the system 'user friendly'.



Fig. 1 Architecture of an Expert System

There are diverse types of expert systems. Diagnosis types of expert systems are used in medical sciences, trouble-shoot electronic or mechanical problems or as a device to rectify the errors. Repair expert systems define repair strategies. Instructional expert systems are used for individualised training. Interpretive expert systems analyse data to determine its importance and utility for future computations.

The knowledge base systems incorporate models of real world scenario. These are used in image examination and speech recognition. Predictive expert systems are used to forecast the possible outcomes of observed situations. This is used in weather forecasting and various forecasting applications. Classification systems are used to classify the sites in the system by the identification of various features through pattern matching process. For example, various types of sites or locations can be classified on the basis of the geography of the area.

Ms. Shubhi Lall Agarwal, Research Scholar, Department of Computer Science, Banasthali Vidyapith, Rajasthan, India

Dr. Vikas Pareek, Associate Professor, Department of Computer Science, Banasthali Vidyapith, Rajasthan, India

III. MEMORY BASED LEARNING

Memory Based Learning (MBL) is a simple function approximation method. Training a memory based learner straight away stock up each data point in memory or database. Making a forecast about the output that will result from input attributes is done by looking for similar points in database. Four components describe a memory based learner: a distance metric, the number of nearest neighbors, a weighting function, and a local model.

IV. IEC WIND CLASS

Turbine wind class is an influential factor which must be well thought-out during the process of setting up a WPP. Wind classes make a decision regarding which turbine that whether it is fit for a wind conditions of a site/location or not. IEC wind class defined by three parameters listed in the table.

The 3 wind classes for wind turbines are standardised by an International Electrotechnical Commission standard (IEC). They are called high, medium and low wind. The wind speed is measured in m/s.

IEC WIND CLASS					
Turbine Class	IEC I High Wind	IEC II Medium Wind	IEC III Low Wind		
Annual Average Wind Speed	10	8.5	7.5		
Extreme 50-Year Gust	70	59.5	52.5		
Turbulence Classes	A 18%	A 18%	A 18%		
	B 16%	B 16%	B 16%		

TABLE 1

V. TURBINE COMPANIES

A list of wind turbines manufactured by Suzlon, Enercon and Vestas are used as database. Sample data of Suzlon is taken in the paper.

SUZLON								
Name	Rated Power	Rotor Diameter (m)	Swept Area (m ²)	Hub Height (m)	Cut-In Wind Speed (m/s)	Rated Wind Speed (m/s)	Cut Out Wind Speed (m/s)	Wind Class
s52 -600 kw	600 kw	52	2124	75	4	13	25	II A
s66 mark II -1.25 MW	1.254 MW	66	3421	74.5	4	12	20	III A

TABLE 2 LIST OF WIND TURBINES

All the details are stored in a database file which is accessed through a program.

VI. ROUGHNESS CLASS AND ASSOCIATED LANDSCAPES

In general, the higher the roughness at a site, the more the wind will be slowed down by the obstacles like trees, buildings etc.

Metropolitan cities actually slow the wind speed, whereas solid paved runways in airports will only slow the wind to a slight extent. Water surfaces have the smoothest surface.Long grass, shrubs and bushes will slow the wind down considerably.

TABLE 3

ROUGHNESS CLASS AND ASSOCIATED LANDSCAPES

Roughness class	Landscape/location/site				
0	Ocean and huge undisturbed lakes				
0.5	Grass fields, airport runway, highways without buildings and extremely smooth surface				
1	Open agricultural area without boundary wall or fences, very few scattered houses. Rounded hills				

1.5	Agricultural land with few houses and 8				
	1250 meters				
	1250 meters				
2	Agricultural land with few houses and 8				
	meter tall hedge rows in a radius of 500				
	meters				
3	Rural area, small city, agricultural land				
	with tall hedgerows, forests and				
	extremely rough and irregular terrain				
	with uneven heights.				
3.5	Metropolitan cities with multi-storeyed				
	buildings				

VII. A RELATIONSHIP BETWEEN THE ROUGHNESS CLASSES AND IEC WIND CLASSES

Figure 2 depicts a contrast between the roughness classes and IEC wind class. This is in general used to classify wind in Denmark and it shows a relationship between classes and the IEC wind turbine classes (I to IV) and IEC turbulence intensity classes (A and B). [2]

Figure 2 depicts the relationship between roughness classes and the IEC wind turbine classes (I to IV) and IEC turbulence intensity classes (A and B).

Local installation	DS roughness class versus IEC wind turbine class and turbulence class					
at	DS roughness class 0		DS roughness class I		DS roughness class II	
Hub Height h (m)	h<50	h>50	h<80	h>80	h<130	h>130
< 25 km from the North Sea	IEC 2B	IEC 1B	IEC 2B	IEC 1B	IEC 2A	IEC 2B
> 25 km from the North Sea	IEC 2B	IEC 2B	IEC 3B	IEC 2B	IEC 3A	IEC 2B
Ocean	IEC 1B	IEC 1B		-		

Fig. 2: A table published in Danish proceedings showing relationship between roughness class and wind class of a turbine.

The location can be diagnosed from the roughness class. The location can the further be queried for hub height. The list of selected turbines can be selected for the final estimation of power output.

VIII. ANN TECHNIQUES AND LEARNING METHODS

The questions to check the roughness class and perform pattern matching are entered as an input in the perceptron. This perceptron accepts the weighted sum of product of the parameters and the weights associated to it. The weighted sum is compared with n i.e. number of inputs in terms of questions. N is the threshold value. Every question is assigned a weight as 1 for true and 0 for false. If the weighted sum is 90% of n then 10% is added as bias and the class is decided for a particular site.

Question	parameter	Weight	$V_1 \ge w_1$
1	1	1	1
2	1	1	1
	•	•	
n	1	1	n

TABLE 3 Weighted values for questions

IX. BINARY PERCEPTRON FOR THE EXPERT SYSTEM DECIDING ROUGHNESS LENGTH

This algorithm is to design a neuron which takes 5 input as questions and predict the roughness length after pattern matching. It uses the logic of 0 and 1 to train the neural network. Hence it is non differentiable. The algorithm is a modelling of neuron with black box programming logics.

The roughness length can further be used to evaluate the associated roughness class. These roughness classes can be further associated to wind turbine classes. Taking the hub height and the temperature of the site, the air density can be computed.



X. CONCLUSIONS

The paper thus devised a novel technique which uses the roughness length, IEC wind class details and based on the details, it can deduce the roughness class. The paper can use the techniques of artificial neural network, memory based learning, and knowledge based expert system and back propagation techniques to simulate a novel expert system. The system can take inputs from the user in term of wind class and decide upon the IEC wind class. The IEC wind class can be further used to find the roughness class of a terrain and sites are applicable for a turbine.

ACKNOWLEDGMENT

We acknowledge Mr. Vaibhav Mogre of windworldIndia (windpro) for his valuable input. We also thank Dr. Srikantha Rao, Director, TIMSCDR Mumbai, for discussing simulation process at length.

REFERENCES

- [1] <u>https://www.osha.gov/OshDoc/data_General_Facts/carbonmo</u> <u>noxide-factsheet.pdf</u>
- [2] http://proceedings.ewea.org/ewec2006/allfiles2/0292_Ewec2006full paper.pdf, From National Approval Scheme To International Certification Scheme Erik R. Jørgensen, Jørgen Lemming, Risø National Laboratory
- [3] Using Neural Networks to Estimate Wind TurbinePower Generation, Shuhui Li, Member, IEEE, Donald C. Wunsch, Senior Member, IEEE, Edgar A. O'Hair, and Michael G. Giesselmann, Senior Member, IEEE, IEEE Transactions on Energy Conversion, Vol. 16, No. 3, September 2001
- [4] Short term wind power forecasting using hybrid intelligent systems, M. Negnevitsky, Member, IEEE, P. Johnson, Student Member, IEEE and S. Santoso, Senior Member, IEEE, Available from : eprints.utas.edu.au/4821/1/4821.pdf?origin=publication_detailhttp: //ieeexplore.ieee.org
- [5] Soft Computing Applications in Wind Power Systems: A Review and Analysis,Imad Alsyoufa and Ahmad Alzghoulb,Available from : http://proceedings.ewea.org/offshore2009/allfiles2/159_EOW2009 presentation.pdf

Dr. Vikas Pareek is an Associate Professor in the department of computer Science at Banasthali University, India. He is actively engaged in the research on Information security, Electronic commerce, Mobile computing and other related disciplines.

Shubhi Lall Agarwal is a research scholar in the department of computer Science at Banasthali University, India. She has written many books on Computer Science and has taught MCA students in TIMSCDR, Mumbai for 6 years.