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# Wind Speed Prediction using Neural Network

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*Abstract : The wind energy generation has been increasing rapidly in the past few years, making it imperative to know about the variables and the problems involved beforehand. The wind speed is a random variable and it depends on various atmospheric factors. This paper introduces a method to predict the wind speed effectively by making use of the algorithms of Artificial Neural Networks (ANN) and Support Vector Machine (SVM) in MATLAB. Data from Galicia, Spain was used to prepare valid dataset to train the neural network and a complex-valued neural network has been applied to build a model to predict wind speed. The results of the model show that the predicted data is close to the actual wind data available.*

*Keywords: Wind Power, Wind Speed, Artificial Neural Networks, Green Energy, Support Vector Machines (SVM).*

## I. Introduction

Wind is a form of green energy. Wind is caused because of non-uniform heating of earth's surface. Different geographical aspects play an important role in determining the wind speed patterns. Wind flow is used to drive the wind turbines leading to the production of clean energy.

Wind is a clean form of energy but its regulation poses an insuperable problem before the energy engineers. The involvement of all the variables makes it almost impossible to predict wind speeds using simple methods or techniques. If the total output of a wind power plant (WPP) can be predicted with high accuracy, more useful information can be provided to the power companies to help in scheduling power generation. Thus allowing efficient use of Wind energy. Different methods have been adopted in the past to measure and predict the wind speed including statistical and physical methods which include the positioning of sensors and manual calculations based on the data obtained from different sensors positioned at numerous locations. The quality of hardware, accuracy of calculation, computation time delays and sampling rates define the efficacy of the final result. Also the computations cannot always be infallible. Therefore, better results demand for a better prediction system and mostly on the data already made available. This paper makes use of a technique known as Artificial Neural Networks to predict the trends in wind speed by making use of the historical data which is already available.

A number of studies have already been conducted in the past two decades in the area of forecasting green energy. Studies in the past shows conventional methods in forecasting. Later research in area of forecasting include machine learning, neural networks and support vector machine by train the network followed by prediction of green energy. Some of the earlier studies are given below:

In 1959, **Bernard Widrow** and Marcian Hoff of Stanford developed models they called ADALINE and MADALINE. These models were named for their use of Multiple ADAptive LINear Elements. MADALINE was the first neural network to be applied to a real world problem. It is an adaptive filter which eliminates echoes on phone lines. This neural network is still in commercial use. Unfortunately, these earlier successes caused people to exaggerate the potential of Neural Networks, particularly in light of the limitation in the electronics then available. This excessive hype, which flowed out of the academic and technical worlds, infected the general literature of the time. Disappointment set in as promises were unfilled. Also, a fear set in as writers began to ponder what effect "thinking machines" would have on man. Asimov's series on robots revealed the effects on man's morals and values when machines where capable of doing all of mankind's work. Other writers created more sinister computers, such as HAL from the movie 2001.These fears, combined with unfulfilled, outrageous claims, caused respected voices to critique the neural network research. The result was to halt much of the funding. This period of stunted growth lasted through 1981.

In 1982, interest in the field was renewed. John Hopfield of Caltech presented a paper to the National Academy of Sciences. His approach was to create more useful machines by using bidirectional lines. Previously, the connections between neurons were only one way. That same year, Reilly and Cooper used a "Hybrid network" with multiple layers, each layer using a different problem-solving strategy. Also in 1982, there was a joint US-Japan conference on Cooperative/Competitive Neural Networks. Japan announced a new Fifth Generation effort on neural networks, and US papers generated worry that the US could be left behind in the field. (Fifth generation computing involves artificial intelligence. First generation used switches and wires, second generation used the transistor, third state used solid-state technology like integrated circuits and higher level programming languages, and the fourth generation is code generators.) As a result, there was more funding and thus more research in the field.

In 1986, with multiple layered neural networks in the news, the problem was how to extend the Widrow-Hoff rule to multiple layers. Three independent groups of researchers, one of which included David Rumelhart, a former member of Stanford's psychology department, came up with similar ideas which are now called back propagation networks because it distributes pattern recognition errors throughout the network. Hybrid networks used just two layers, these back-propagation networks use many. The result is that back-propagation networks are "slow learners," needing possibly thousands of iterations to learn.

In 1962 **Rosenblatt** (Rosenblatt, 1962) explored a different kind of learning machines: perceptrons or neural networks. The perceptron consists of connected neurons, where each neuron implements a separating hyperplane, so the perceptron as a whole implements a piecewise linear separating surface. See Fig. 1. No algorithm that minimizes the error on a set of vectors by adjusting all the weights of the network was found in Rosenblatt's time, and Rosenblatt suggested a scheme where only the weights of the output unit were adaptive. According to the fixed setting of the other weights the input vectors are non-linearly transformed into the feature space, Z, of the last layer of units. In this space a linear decision function is constructed.

An algorithm that allows for all weights of the neural network to adapt in order locally to minimize the error on a set of vectors belonging to a pattern recognition problem was found in 1986 (Rumelhart, Hinton & Williams, 1986,1987; Parker, 1985; LeCun, 1985) when the backpropagation algorithm was discovered. The solution involves a slight modification of the mathematical model of neurons. Therefore, neural networks implement "piece-wise linear type" decision functions. In this article we construct a new type of learning machine, the so-called support-vector network. The support-vector network implements the following idea: it maps the input vectors into some high dimensional feature space Z through some non-linear mapping chosen a priori. In this space a linear decision surface is constructed with special properties that ensure high generalization ability of the network.

**Warren Sturgis McCulloch** (November 16, 1898 – September 24, 1969) was an American neurophysiologist and cybernetician, known for his work on the foundation for certain brain theories and his contribution to the cybernetics movement. In the 1943 paper they attempted to demonstrate that a Turing machine program could be implemented in a finite network of formal neurons (in the event, the Turing Machine contains their model of the brain, but the converse is not true), that the neuron was the base logic unit of the brain. In the 1947 paper they offered approaches to designing "nervous nets" to recognize visual inputs despite changes in orientation or size. From 1952 he worked at the Research Laboratory of Electronics at MIT, working primarily on neural network modelling. His team examined the visual system of the frog in consideration of McCulloch's 1947 paper, discovering that the eye provides the brain with information that is already, to a degree, organized and interpreted, instead of simply transmitting an image.

## II. RESEARCH METHODOLOGY

Artificial Neural Networks (ANN)

It is the method that consists of networks of many simple processors (units) operating in parallel, each possibly having a small amount of local memory. A *multilayer perceptron* neural network, with feedforward architecture with three layers of units is used due to its status and capacity to solve large amount of problems. The algorithm used for the training is the well-known *back-propagation* method (Haykin, 2003). Fig 1 depicts the feed-forward neural network which is used. This neural network shows the first layer (layer A) and the second layer (layer B), which are called hidden layers. This network has one unit in the third layer (layer C), which is called the outputlayer. Each unit has an extra input that is assumed to have a constant value of one. The weight that modifies this extra input is called the bias. Data propagate along the connections in the direction from the network inputs to the network outputs, hence the term *feed-forward* (Negnevitsky, 2002).

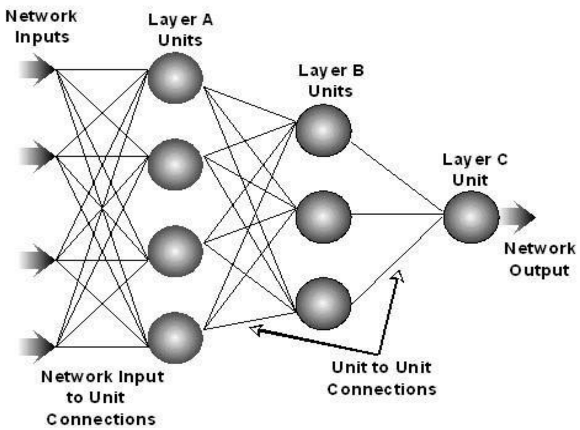


Fig 1. Structure of a typical neural network

A key concept required for defining a linear classifier is the *dot product* between two vectors

$$\langle \mathbf{w}, \mathbf{x} \rangle = \sum_{j=1}^{M} w_j x_j,$$

also referred to as the *inner product* or *scalar* product.
A linear classifier is based on a linear *discriminant function* of the form

$f(\mathbf{x})$ = h**w**.**xi** + *b*. (1)

The discriminant function $f(\mathbf{x})$ assigns a "score" for the input **x**, and is used to decide how to classify it. The vector **w** is known as the *weight vector*, and the scalar $b$ is called the *bias*. In two dimensions the points satisfying the equation h**w**, **xi** = 0 correspond to a line through the origin, in three dimensions a plane and more generally a *hyperplane*. The hyperplane divides the space into two half spaces according to the sign of $f(\mathbf{x})$, which indicates the side of the hyperplane a point is located on the figure. If $f(\mathbf{x}) > 0$, then one decides for the positive class, otherwise for the negative. The boundary between regions classified as positive and negative is called the *decision boundary* of the classifier.

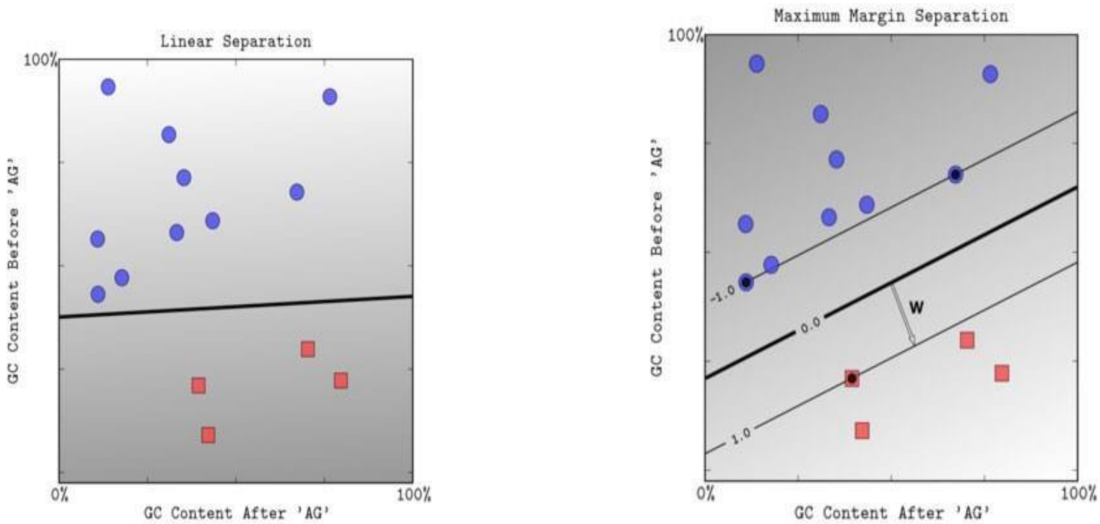


Fig 2.A typical Scatter Plot

III. RESULTS AND DISCUSSIONS

Results 1st -7th January are shown in figures 3-4 and 1st- 7thJuly are shown in figures 5-6

**1ST- 7th January**

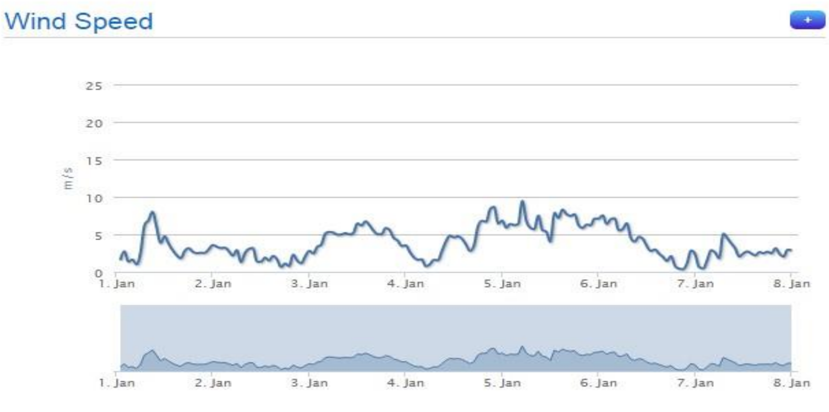


Fig 3.Windspeed vs. Date

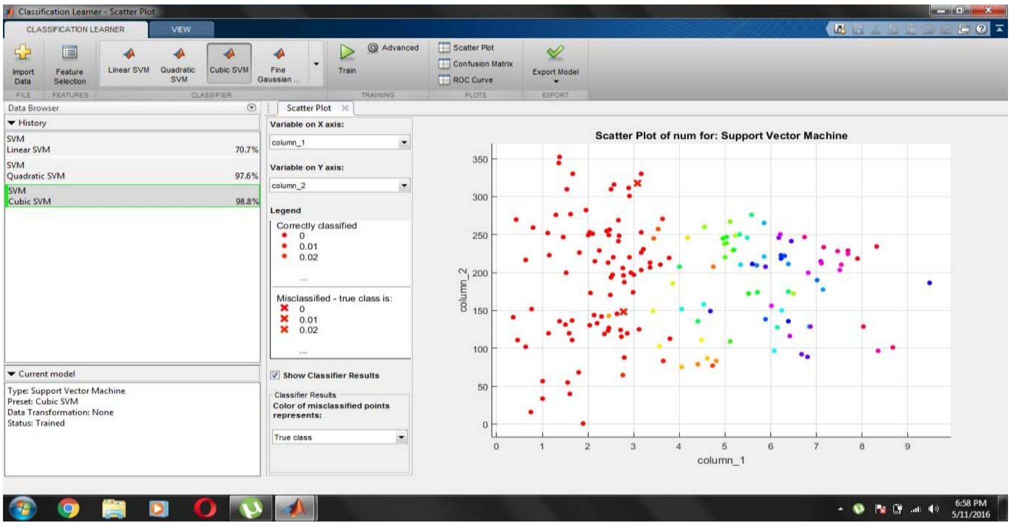


Fig 4.Scatter plot

1st-7thJuly

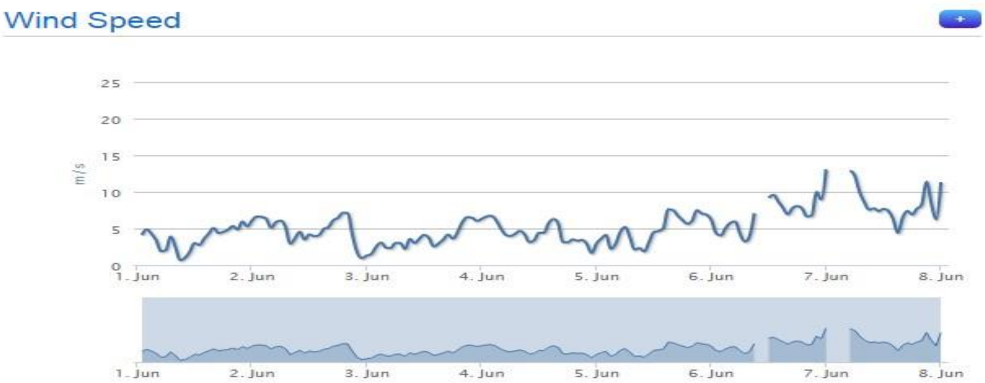


Fig 5.Windspeed vs. date

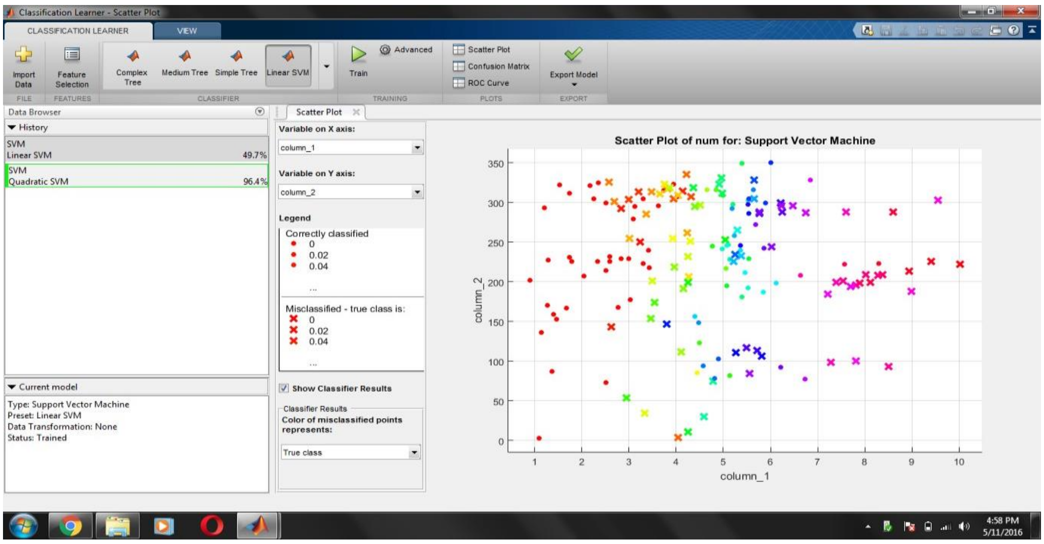


Fig 6. Scatter plot

The ANN toolbar used to train the network yielded better results on increasing the number of neurons present in the model. Also the more the number of samples of the given variables related to wind speed, the more accurate was the result obtained. In this paper the wind data over a period of two years was compiled and tested against the original and finally SVM classifier was used to predict the wind speed which was compared with the original data available.

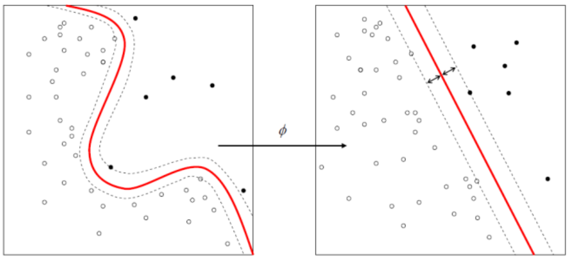


Fig 7. Scatter plot showing division of data on either sides of the hyper plane

The separation achieved is good by the hyperplane that has the largest distance to the nearest training-data point of any class (so-called functional margin), the larger the margin the lower the generalization error of the classifier.

## IV. CONCLUSIONS

This paper uses SVM and ANN toolbar for windspeed prediction. It compares the results from the network (trained using Neural Network) with original data over a period of two years. Smother error in the predicted data was 1.2% and 3.2 % for the periods $1^{st}$-$7^{th}$ January and $1^{st}$-$7^{th}$ July respectively. The findings of this paper indicate that the methods adopted to predict the speed of the wind produced desired results and that the error in the predictions was low.

## REFERENCES

1. M. Lange, “On the uncertainty of wind power predictions analysis of the forecast accuracy and statistical distribution of errors,” Journal of Solar Energy Engineering, vol.127, no. 2, pp. 177-194, 2005.
2. C. Monterio, R. Bessa, and V. Miranda. Wind Power Forecasting: State of-the-Art 2009, Argonne National Laboratory, 2009.
3. G. Giebel, J. Badger, L. Landberg, H. Nielsen, H. Madsen, K. Sattler, H. Feddersen, H. Vedel, J. Tøfting, L. Kruse, and L. Voulund, “Wind power prediction using ensembles,” Risø National Laboratory, Roskilde, Denmark, 2005.
4. J. Wang, A. Botterud, V. Miranda, C. Monteiro and G. Sheble, “Impact of wind power forecasting on unit commitment and dispatch,” in Proc. 8th Int. Wind Integration Workshop, Bremen, Germany, 2009.
5. L. Ma, S.Y. Luan, C.W. Jian, H.L. Liu, and Y. Zhang, “A review on the forecasting of wind speed and generated power,” Renewable and Sustainable Energy Reviews, vol. 13, pp. 915-920, 2009.
6. J.L Torres, A. Garcia, M. De Blas, and A. De Francisco, “Forecast of hourly average wind speed with ARMA models in Navarre (Spain),” Solar Energy, vol. 79, pp. 65-77, 2005.
7. J.P.S. Catalao and V.M.F. Mendes, “An artificial neural network approach for short-term wind power forecasting in Portugal”, in Proc. 15th International Conference on Intelligent System Applications to Power System, vol. 17, no. 1, 2009.
8. G.N. Kariniotakis, G.S. Stavrakakis, and E.F. Nogaret, “Wind power forecasting using advanced neural networks models,” IEEE Trans. Energy Conversion, vol. 11, no. 4, pp. 762-767, 1996.
9. G. Sideratos and N.D. Hatziargyriou, “An advanced statistical method for wind power forecasting,” IEEE Trans. Power System, vol. 22, no. 1, pp. 258-265, 2007.
10. P. Pinson and G.N. Kariniotakis, “Wind power forecasting using fuzzy neural networks enhanced with on-line prediction risk assessment,” in Proc. IEEE Bologna Power Tech Conference Proceeding, vol 2. 2003.
11. M.A. Mohandes, S. Rehman, and T.O. Halawani, “A neural networks approach for wind speed prediction”, Renewable Energy, vol. 13, pp. 345-354, 1998.
12. M.A. Mohandes, T.O. Halawani, S. Rehman, and A. Hussain, “Support Vector Machines for wind speed prediction,” Renewable Energy, vol. 29, no. 6, pp.939-947, 2004.
13. H.Y. Zheng and A. Kusiak, “Prediction of wind farm power ramp rates: A data-mining approach,” ASME Journal of Solar Energy Engineering, vol. 131, pp. 031011-1-031011-8, 2009.
14. K. Speelakshmi and P.R. Kumar, “Performance evaluation of short term wind speed prediction techniques,” International Journal of Computer Science and Network Security, vol. 8, no. 8, pp. 162-169, 2008.
15. I.T. Nabney, Netlab Algorithms for Pattern Recognition, Verlag, Springer Press, pp. 191-198, 2002.
16. K.R. Miller and V. Vapnik, Using Support Vector Machine for Time Series Prediction, Cambridge: MIT press, pp. 243-253. 1999.
17. A. Smola and B. Schölkopf, “A tutorial on support vector regression,” Statistics and Computing, vol. 14, no. 2, pp. 199-222, 2003.
18. C.W. Potter, D. Lew, J. McCaa, S. Cheng, S. Eichelberger, and E. Grimit, “Creating the dataset for the western wind and solar integration study (U.S.A),” in Proc. 7th International Workshop on Large Scale Integration of Wind Power and on Transmission Networks for Offshore Wind Farms, Madrid, Spain, May 26-27, 2008.
19. C.W. Potter, H. A. Gil, and J. McCaa, “Wind power data for grid integration studies,” in Proc. 2007 IEEE Power Engineering Society General Meeting, Tama, FL, USA. 2007.
20. Long-term and medium-term development of renewable energy, State council of the People's Republic of China. 2007.
21. Y-K Wu, and J-S Hong, “A literature reviews of wind forecasting technology in the world,” IEEE Power Tech 2007, Lausanne, pp. 504-509, 2007.
22. H. Lund, “Large-scale integration of wind power into different energy systems,” Energy, vol. 30, no. 13, pp. 2402-2412, 2005.

23. H. Holttinen, B. Lemström, P. Meibom, H. Bindner, A. Orths, F. Van Hulle, C. Ensslin, A. Tiedemann, L. Hofmann, W. Winter, A. Tuohy, M. O'Malley, P. Smith, J. Pierik, J.O. Tande, A. Estanqueiro, E. Gomez, L. Söder, G. Strbac, A. Shakoor, J.C. Smith, P. Parsons, M. Milligan, Y. Wan, Design and Operation of Power Systems with Large Amounts of Wind Power, State of the art report, VTT Working Papers 82, Espoo, Finland, 2007.

24. Short-term prediction of local wind conditions Journal of Wind Engineering and Industrial Aerodynamics, 89, pp. 235–245 ,2001.

25. Sa'nchez Short-term prediction of wind energy production International Journal of Forecasting, 22 pp. 43–56 , 2006.

26. C. Potter, M. Ringrose, and M. Negnevitsky, "Short-term wind forecasting techniques for power generation", Proceedings of the Australasian Universities Power Engineering Conference, Brisbane, Australia, 2004.

27. S. Salcedo-Sanz, A.M. Perez-Bellido, E.G. Ortiz-Garcia, A. Portilla- Figueras, L. Prieto, D. Paredes, "Hybridizing the fifth generation mesoscale model with artificial neural networks for short-term wind speed prediction" Renewable Energy, 34 (6) pp. 1451–1457, 2009.

28. G. Kariniotakis, I. Marti, What Performance Can Be Expected by Short-term Wind Power Prediction Models Depending on Site Characteristics", CD-Rom proceedings of the European Wind Energy Conference EWEC 2004, London, UK , 22-25 Nov. 2004.

29. T.G. Barbounis, J.B. Theocharis, M.C. Alexiadis, P.S. Dokopoulos "Long-term wind speed and power forecasting using local recurrent neural network models" IEEE Trans. Energy Convers, 21 (1) pp. 273–284, 2006.