VIBRATION SIGNALS PROCESSING BY CELLULAR AUTOMATA FOR WIND TURBINES INTELLIGENT MONITORING

Tomasz BARSZCZ*, Andrzej BIELECKI**, Mateusz WÓJCIK***

* AGH University of Science and Technology,
Faculty of Mechanical Engineering and Robotics, Chair of Robotics and Mechatronics,
Al. Mickiewicza 30, 30-059 Cracow, Poland, e-mail: tbarszcz@agh.edu.pl
** AGH University of Science and Technology,
Faculty of Electric Engineering, Automation, Computer Science and Biomedical Engineering,
Chair of Applied Computer Science, Al. Mickiewicza 30, 30-059 Cracow, Poland,
e-mail: azbielecki@gmail.com
*** Jagiellonian University, Faculty of Physics, Astronomy and Applied Computer Science
Reymonta 4, 30-059 Cracow, Poland, e-mail: mateusz.wojcik@uj.edu.pl

Summary

In recent years wind energy is the fastest growing branch of the power generation industry. The largest cost for the wind turbine is its maintenance. A common technique to decrease this cost is a remote monitoring based on vibration analysis. Growing number of monitored turbines requires an automated way of support for diagnostic experts. As full fault detection and identification is still a very challenging task, it is necessary to prepare an early-warning tool, which would focus the attention on cases which are potentially dangerous. There were several attempts to develop such tools, in most cases based on various classification methods. The techniques that have been used so far are based on the vibration signals analysis in which the signals are considered as time series. However such approach has crucial limitations. Therefore, new approaches for wind turbines intelligent monitoring are worked out. Artificial intelligence systems are ones of promising. In this paper such approach is proposed - a vibration signal spectrum is considered as a pixel matrix which is processed using deterministic cellular automaton (DCA). It turns out that such processing allows us to detect pre-failure states.

Keywords: cellular neural networks, wind turbines, gears, intelligent monitoring

PRZETWARZANIE SYGNAŁÓW DRGANIOWYCH PRZY POMOCY AUTOMATÓW KOMÓRKOWYCH W CELU INTELIGENTNEGO MONITORINGU TURBIN WIATROWYCH

Streszczenie

W ostatnich latach energetyka wiatrowa jest najszybciej rozwijającą się gałęzią przemysłu energetycznego. Najkosztowniejsza w turbinach wiatrowych jest ich konserwacja. Popularną techniką obniżającą te koszta jest zdalny monitoring bazujący za analizie wibracyjnej. Rosnąca liczba monitorowanych turbin zmusza do znalezienia automatycznego wsparcia dla diagnozujących ekspertów. Ponieważ pełna detekcja i identyfikacja uszkodzeń jest wciąż wielkim wyzwaniem, potrzebne jest określenie narzędzia zdolnego wychwytywać jak najwcześniejsze symptomy awarii. Podejmowane były próby stworzenia takich narzędzi, opierając się na różnych metodach klasyfikacji. Używane techniki od dłuższego czasu bazują na analizie sygnałów wibracyjnych, które rozpatrywane są jako szeregi czasowe. Takie podejście, jednakże, ma istotne ograniczenia. Dlatego też poszukuje się nowych metod, które mogą być skutecznie użyte do inteligentnego monitoringu turbin wiatrowych. Systemy sztucznej inteligencji wydają się być obiecującym podejściem. W niniejszej publikacji testowana jest użyteczność tego podejścia - badane widmo sygnału wibracyjnego jest rozumiane jako macierz komórek, które konstytuują automat komórkowy. Przetwarzanie sygnałów przy pomocy powyższego automatu pozwoli wykrywać stany przedawaryjne.

Słowa kluczowe: deterministyczne automaty komórkowe, turbiny wiatrowe, przekładnie, inteligentny monitoring

1. INTRODUCTION

In recent years wind energy is the fastest growing branch of the power generation industry. The average yearly growth in the years 1997-2003 achieved 32% in the United States and 22% in the European Union [6] and these figures will hold for at least the next decade. The distribution of costs during the life cycle of the unit for wind energy is significantly different from that of traditional, fossil fired units [6]. First of all, initial investment costs are relatively higher, whereas in traditional units cost of fuel plays important role - usually it is the second largest cost. After commissioning, the largest cost for a wind turbine (WT for abbreviation) is its maintenance. With proper maintenance policies, wind turbines can achieve the highest level of availability in the power generation sector - even up to 98%.

Studies have shown that approximately 80% of all fractures are caused by machinery fatigue and only 20% by a static overload. Therefore, studies concerning variations of operational conditions in a wind turbine mechanical system are crucial for their engineering. Such studies have important practical application, as the wind turbine maintenance, as it has been mentioned, generates the largest part of the cost of its operation [18]. A common technique to decrease this cost is a condition monitoring [17,20,21,27], first of all continuous monitoring of the drivetrain of a wind turbine. Therefore, condition monitoring of wind turbines, including fault diagnostics, in particular at the early stage of a fault occurrence or even participatory actions, is an essential problem in wind turbines engineering in particular [17,20,24] and in rotating machinery engineering in general [3]. There were several attempts to develop various monitoring tools, in most cases based on various classification methods. Some of them are based on artificial neural networks (ANNs for abbreviation).

So far the techniques that has been used for gears monitoring are based on the vibration signals analysis in which the signals are considered as time series. However in this paper a vibration signal spectrum is considered as a pixel matrix which is processed using deterministic cellular automaton (DCA for abbreviation) - basic information about DCA and cellular ANNs, that are complex version of DCAs, can be found in [13,14,15,16,22,23,26]. Such processing allows us to detect pre-failure states.

This paper is a continuation of studies concerning monitoring wind turbines states [1,4,19], modelling its loads [2,12] and monitoring and diagnosis gears faults [6,7,8,9,10,11,28].

This article is organizing in the following way. In Section 2 wind turbines mechanics is described. Basic facts concerning deterministic cellular automata are briefly recalled in Section 3. The proposed approach and results are presented in Section 4.

2. WIND TURBINE MECHANICS

The faults which are sought in wind turbines are primarily of mechanical origin. The wind turbine with the gearbox, which is the most popular type, can be described in the following way. The main rotor with three blades is supported by the main bearing and transmits the torque to the planetary gear. The main rotor is connected to the plate which is the gear input. The planetary gear has three planets, with their shafts attached to the plate. The planets roll over the stationary ring and transmit the torque to the sun. The sun shaft is the output of the planetary gear. The sun drives the two-stage parallel gear which has three shafts: the slow shaft connected to the sun shaft, the intermediate shaft and the fast shaft, which drives the generator. The overall gear ratio is in the range of 1:100. The generator produces alternating current of slightly varying frequency. This current is converted first into direct current power and then into alternating current power of frequency equal to the grid frequency. Electric transformations are performed by the controller at the base of the tower - see Fig.1.

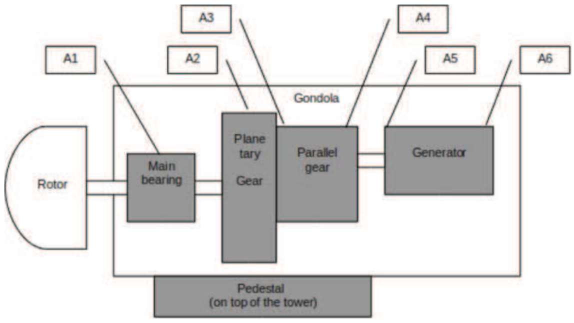

Figure 1: The mechanical structure of the wind turbine. Location of vibration measurement sensors is shown by An symbols

In the field of vibrodiagnostics, a machine operational state is understood as an accepted range of machines operational points enabling referential analysis. In practice, machine operating point is defined by values of available measurements of physical quantities such as speed, load, pressure, temperature, etc., usually called machine process parameters [19]. Typically, from each vibration record, a set of diagnostic indicators is calculated known as trends. Each trend point is a combination of representation of true machine technical condition and behaviour, machines current operating point, measurement error and random factor. In a typical condition monitoring set up, each trend is tracked against a pre-calculated threshold value. In this case, operational states (shortly called states) are used for data classification during the data acquisition process. On the basis of these states, data is combined into sets, which are assumed to represent a particular machine. Consequently, the overall number of defined diagnostic indicators and estimators is equal to the number of indicators and estimators multiplied by the number of states. Therefore, from operators point of view, it is desirable to have as little states as possible. On the other hand, from reliable-diagnostics point of view, in order to minimize the fluctuation of machines operating points, it is desirable to define ranges of states as low as possible. In this case, the state configuration would result either in single operational state with low permissible fluctuation of operational parameters or in a large number of operational state with low permissible fluctuations of operational parameters.

3. DETERMINISTIC CELLULAR AUTOMATA

In DCAs, that are the simples type of cellular automata, the spatial domain of the model is divided into a fix lattice and each lattice point, a cell, has a state associated with it. The cell state at the next time step is determined solely from the earlier state of the cell and its neighbours. The lattice of cells can have any dimension but two-dimensional DCAs are considered most frequently and such DCA is used in the experiment described in this paper. The used DCA is also an automaton with completely defined rules. This means that if the initial state of the automaton is known, all subsequent states are found by iterating and updating synchronously. In these types of automata each state of the whole automaton is an array of states of cells. As it has been mentioned, cells influence and are influenced by neighbours, in the simplest cane the nearest ones. However, a neighbourhood in two dimensions can be defined in several different ways. In a square lattice both only four cells, conventionally addressed as points of the compass by N,W,E,S, and also the ones that can be reached diagonally: NE,NW,SE,SW can be regarded as the nearest neighbourhood. However, the lattice can have also hexagonal organization and then each cell has six nearest neighbours. The general rule of an cellular automaton evolution is given by the equation

$$C_{t+1}(i)=F(C_{t+1}(i), C_{t+1}(j)), \quad (1)$$

where $C_{t+1}(i)$ denotes the state of the *i*-th cell at the *t*-th iteration. The index *j* numerates cells from the neighbourhood that is taken into consideration. Each cell can take only the finite number of states. In the simplest cellular automata, the binary ones, each cell can be only in one of the two states: 0 or 1.

4. RESULTS

The used data are real ones recorded on a 1.5 MW wind turbine, located in Germany. The data were available courtesy of the company SeaCom GmbH from Herne, Germany. The measurement system consisted of signal conditioning unit (PA8000D type form EC Electronics), data acquisition card (USB-6210 type from National Instruments) and dedicated data acquisition software. The software was developed in the LabView environment and run on the ARK-3384 embedded computer. The measured wind speed signal was acquired from the wind turbine controller. The system also has acquired the turbine output power and six vibration channels. A CA has been applied to processing signals obtained from the single vibration channel.

A fault classification system for vibration signals was created using a cellular automaton. System classifies time series of vibration signals. That series can be presented in the form of charts. A cellular automaton is designed to process that charts.

The automaton is based on a two-dimensional square lattice of cells with radius of neighbourhood equal to 1. The network topology is defined in such a way, that all the cells N,W,S,E,NW,NE,SW,SE constitute the neighbourhood - see Fig.2. Each cell has a binary value (0 or 1). The cell value represents a segment of the chart. Network is constructed using mentioned rules and after that the classification is being done in steps described in following subsections.

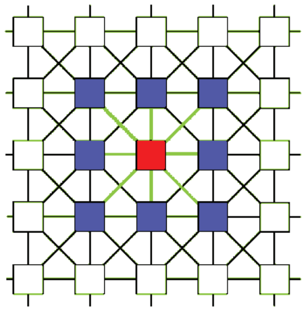

Figure 2: Two-dimensional DCA with radius of neighbourhood r=1: the red cell has nine neighbours - the eight blue cells and itself

The example of the vibration signal is presented in Fig.3. This time series can be divided into three intervals. The first one corresponds to the constant average trend. In the second one the average trend increases whereas in the third one the average trend has a constant value but grater than the value on the average trend in the first interval. The second interval corresponds to the failure. Therefore, the intelligent monitoring system should recognize the border between the first and the second interval as the pre-failure state.

4.1. Network initialization

The vibration signals chart is considered to be a visual pattern, not a numerical time series. Thus, it is regarded to be a binary matrix. The size of a grid cell is determined manually. Cell length and width can be different. Each grid cell reflects one network cell. If there is an experimental point inside the grid cell then that network cell is selected and is marked as 1. An example of network cells is presented in Fig.3.

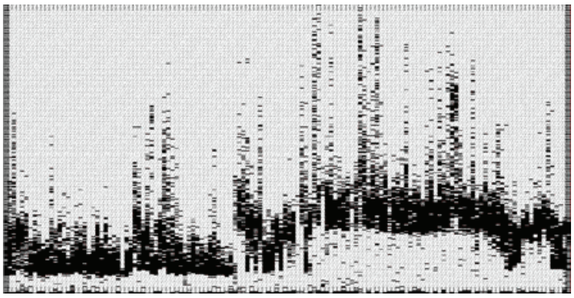

Figure 3: The DCA after initialization

4.2. Network processing

After initialization the network changes states of cells in an iteration process. Transfer function of cells is defined as the Surface Tension rule. The rule of the evolution of a cell state, defined in general by the formula (1), is given in such a way that the state of each cell $C_{t+1}(i)$ in the iteration (t+1)-th is equal to:

- 0, when a sum of cells neighbouring to the cell c_t (including that cell) is one of the following: 0, 1, 2, 3 or 5,
- 1, otherwise.

After a specified number of iterations the processing is stopped.

4.3. Final rating

At the final state dominate and separate groups of cells having value 1 are counted. If there is more then one group then it means that some fault occurred. Periods of time in which the fault could have occurred are points of the time series having no cells with value equal to 1. Counting is done manually, but some algorithms to do that automatically could be specified.

A few steps of a cellular automaton state evolution are presented in figures 4, 5 and 6. There are two dominate separate groups of cells, therefore data can be marked as having a fault. The border between two obtained clusters corresponds - see Fig.6 - corresponds to the point when the average trend starts to increase - see Fig.3. Thus, the CA recognized the pre-failure state properly.

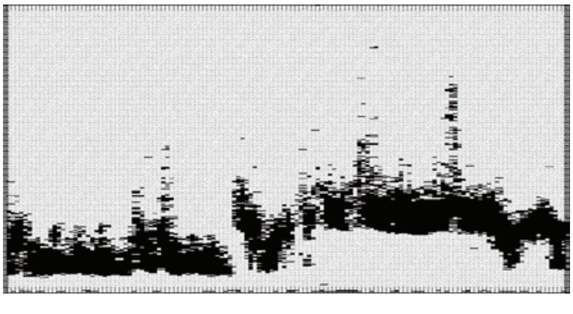

Figure 4: The cellular automaton after the first iteration

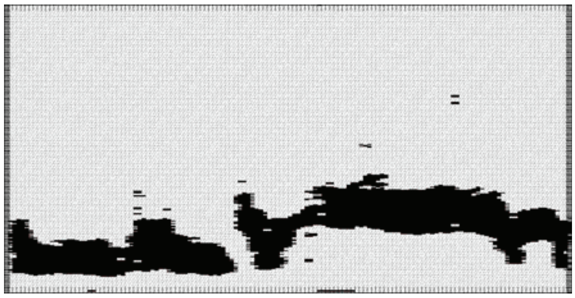

Figure 5: The cellular automaton after 10 iterations

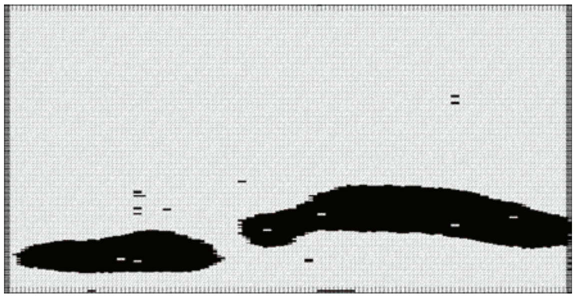

Figure 6: The cellular automaton after 100 iterations

5. CONCLUDING REMARKS

As it has been mentioned, intelligent monitoring is crucial in wind turbines exploitation. On the other hand, there are very few attempts to create system for intelligent monitoring based on artificial intelligence - see [17] and references given there. The experiments described in this paper show that DCAs can be an effective tool for such task performing - the symptoms of a turbine damage can be detected using them. The described approach was based on the simple cellular automaton. The signal processing based on more complex systems of this type, i.e. cellular neural networks [13,14,22,23,25], should be tested as well. It should be stressed however, that the obtained results are preliminary ones – only one vibration channel has been used and, according to the lack of data obtained during the break down moment, only one case has been considered. Usually, a few vibration channels are observed simultaneously - see [2]. The monitoring module based on DCAs is planned to be a module of hybrid expert system for intelligent monitoring and fault diagnostics in wind turbines based on ANNs. Though it is planned that ART-type artificial neural networks will play a crucial role in the intelligent monitoring system, according to the results obtained in [1,4,5], the cellular automata can be used as specialised modules for detecting pre-failure states in bearings.

It should be also mentioned that the method presented in this paper has been referred to gears in wind turbines and the experiment has been performed for vibration data obtained from wind turbines. However, the method can be applied also in any rotational machines working under variable load.

REFERENCES

[1] Barszcz T., Bielecka M., Bielecki A., Wójcik M. *Wind turbines states classification by a fuzzy-ART neural network with a stereographic projection as a signal normalization.* Lecture Notes in Computer Science, vol.6594, 2011, 225-234.

[2] Barszcz T., Bielecka M., Bielecki A., Wójcik M. *Wind speed modelling using Weierstrass function fitted by a genetic algorithm.* Journal of Wind Engineering and Industrial Aerodynamics, vol.109, 2012, 68-78.

[3] Barszcz T., Bielecki A., Romaniuk T. *Application of probabilistic neural networks for detection of mechanical faults in electric motors.* Electrical Review, vol.8/2009, 2009, 37-41.

[4] Barszcz T., Bielecki A., Wójcik M. *ART-type artificial neural networks applications for classification of operational states in wind turbines.* Lecture Notes in Artificial Intelligence, vol.6114, 2012, 11-18.

[5] Barszcz T., Bielecki A., Wójcik M., Bielecka M. *ART-2 artificial neural networks applications for classification of vibration signals and operational states of wind turbine for intelligent monitoring.* Lecture Notes in Computer Science, 2013, accepted.

[6] Barszcz T., Randall R.B. *Application of spectral kurtosis for detection of a tooth crack in the planetary gear of a wind turbine.* Mechanical Systems and Signal Processing, vol.23, 2009, 1352-1365.

[7] Bartelmus W. *Mathematical modelling and computer simulations as an aid to gearbox diagnostics.* Mechanical Systems and Signal Processing, vol.15, 2001, 855-871.

[8] Bartelmus W, Chaari F., Zimroz R., Haddar M. *Modelling of gearbox dynamics under time-varying nonstationary load for distributed fault detection and diagnosis.* European Journal of Mechanics, A/Solids, vol.29, 2010, 637-646.

[9] Bartelmus W. Zimroz R. *Gearbox systems dynamic modelling for diagnostic fault detection.* Proceedings of the ASME Design Engineering Technical Conference, vol.4B, 2003, 625-633.

[10] Bartelmus W., Zimroz R. *Vibration condition monitoring of planetary gearbox under varying external load.* Mechanical Systems and Signal Processing, vol.23, 2009 246-257.

[11] BartelmusW., R. Zimroz R. *A new feature for monitoring the condition of gearboxes in non-stationary operation conditions.* Mechanical Systems and Signal Processing, vol. 23, 2009, 1528-1534.

[12] Bielecka M., Barszcz T., Bielecki A., Wójcik M. *Fractal modelling of various wind characteristics for application in a cybernetic model of a wind turbine.* Lecture Notes in Artificial Intelligence, vol.7268, 2012, 531-538.

[13] Chua L.O., Yang L. *Cellular Neural Networks. Theory,* IEEE Transactions on Circuits and Systems, vol.35, 1988, 1257-1274.

[14] Chua L.O., Yang L., *Cellular Neural Networks. Applications,* IEEE Transactions on Circuits and Systems, vol.35, 1988, 1275-1290.

[15] Codd E.F., *Cellular Automata,* Academic Press Inc., Orlando, 1968.

[16] Ermentrout G.B., Edelstein-Keshet L., *Cellular automata approaches to biological modelling,* Journal of Theoretical Biology, vol.160, 1993, 97-133.

[17] Hameeda Z., Honga Y.S., Choa T.M., Ahnb S.H., Son C.K. *Condition monitoring and fault detection of wind turbines and related algorithms: A review.* Renewable and Sustainable Energy Reviews, vol.13, 2009, 1-39.

[18] Hau E., *Wind turbines: Fundamentals, Technologies, Applications, Economics,* Springer, Berlin, Heidelberg, 2006.

[19] Jabłoński A., T. Barszcz T., *Procedure for data acquisition for machinery working under non-stationary operational conditions,* Proceedings of the Ninth International Conference on Condition Monitoring and Machinery Failure Prevention Technologies, 2012, London.

[20] Jabłoński A., Barszcz T., Bielecka M. *Automatic validation of vibration signals in wind farm distributed monitoring systems.* Measurement, vol.44, 2011, 1954-1967.

[21] Jabłoński A., Barszcz T., Bielecka M., Brehaus P., *Automatic validation of vibration signals in wind farm distributed monitoring systems,* Measurement, vol.46, 2013, 727-738.

[22] Kacprzak T., Ślot K., *Sieci neuronowe komórkowe,* PWN, Warszawa, 1995 (in Polish).

[23] Kosiński R.A., *Sztuczne sieci neuronowe - dynamika nieliniowa i chaos,* WNT, Warszawa, 2002 (in Polish).

[24] Kusiak A., Li W. *The prediction and diagnosis of wind turbine faults.* Renewable Energy, vol.36, 2011, 16-23.

[25] Roska T., Vandewalle J., *Cellular Neural Networks,* Chichester, Wiley & Sons, 1993.

[26] Wolfram S. *Universality and complexity in cellular automata.* Physica D: Nonlinear Phenomena, vol.10, 1984, 1-36.

[27] Zhang Z., Verma A., Kusiak A. *Fault analysis and condition monitoring of the wind turbine gearbox,* IEEE Transactions of Energy Conversion, vol.27, 2012, 526-535.

[28] Zimroz R, Bartelmus W, *Gearbox condition estimation using cyclo-stationary properties of vibration signal,* Key Engineering Materials, vol.413-414, 2009, 471-478.

This paper was supported by the Polish Ministry of Science and Higher Education under grant number N504 147838

Dr hab. inż. **Tomasz BARSZCZ** received the M.Sc. degree in Electric Engineering and Automatic Control from the Technical University of Gdańsk in 1993, Ph.D. in Mechatronics (1997) and D.Sc. in Automation and Robotics in 2009 from the AGH University of Science and Technology. Has long experience of application of research in numerous industries in Poland and abroad. Author of 4 books and over 150 papers. Monitoring systems developed under his supervision were installed on several hundred machines worldwide.

Dr hab. **Andrzej BIELECKI** received the M.Sc. degree in Physics and Mathematics from the Jagiellonian University in 1985 and 1992 respectively, Ph.D. in Mathematics in 1999 and D.Sc. in Mathematics in 2009. Dynamical systems theory, artificial intelligence and cybernetics are the topics of his scientific interest. He is an author of over 70 scientific papers.

Mateusz WÓJCIK, received the MSc degree in Computer Science from the Jagiellonian University. He is a PhD student at the Jagiellonian University, Faculty of Physics, Astronomy and Applied Computer Science. His scientific interests focus on artificial intelligence and machine learning.