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Fault Detection and Diagnosis in dynamic systems using Weightless Neural Networks

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This work examines Fault Detection and Diagnosis (FDD) based on Weightless Neural Networks (WNN) with applications in univariate and multivariate dynamic systems. WNN use neurons based on RAM (Random Access Memory) devices. These networks use fast and flexible learning algorithms, which provide accurate and consistent results, without the need for residual generation or network retraining, and therefore they have great potential use for pattern recognition and classification (Ludermir, Carvalho, Braga, de Souto, 1999). The proposed system firstly executes the selection of attributes (in the multivariable case) and does the time series mapping of the data. In the intermediate stage, the WNN performs the detection and diagnosis per class. The network outputs are then passed through a clustering filter in the final stage of the system, if a diagnosis per fault groups is necessary. The system was tested with two case studies: one was an actual application for the temperature monitoring of a sales gas compressor in a natural gas processing unit; and the other one uses simulated data for an industrial plant, known in the literature as "Tennessee Eastman Process". The results show the efficiency of the proposed systems for FDD with classification accuracies of up to 98.78% and 99.47% for the respective applications.

Abbreviations: ANFIS, Adaptive Neuro-Fuzzy Inference System; ANN, Artificial Neural Net; BA, State of Bahia, Brazil; CW, Counting WiSARD; $Disc_k$, Discriminator k; FCM, Fuzzy C-Means; FDD, Fault Detection and Diagnosis; GA, Genetic Algorithm; HTA, High Temperature Alarm; HHTA, High High Temperature Alarm; kNN, k-Nearest Neighbour; LDA, Linear Discriminant Analysis; MSPCA, Multi-Scale Principal Component Analysis; MTS, Multivariate Time Series; NGPU, Natural Gas Processing Unit; Petrobras, Petróleo Brasileiro S.A.; PIMS, Plant Information Management System; PLS, Partial Least Squares; PW, Pattern WiSARD; QDA, Quadratic Discriminant Analysis; RAM, Random Access Memories; RewPun, REWard/ PUNishment; SES, Simple Exponential Smoothing; SGC, Sale Gas Compressor; SPA, Successive Projections Algorithm; $SPCA_{ms}$, Multiscale PCA Similarity factor; TEP, Tennessee Eastman Process; WiSARD, Wilkes-Stonham-Aleksander Recognition Device; WNN, Weightless Neural Network; $\bar{a}_i$, Average attribute of the t values of the processed series for attribute i; A, C, D, E, Reagents used in TEP; *ACC*, Accuracy; a_h, Original series attribute in period h; $a_{n,t}$, Attribute n of the input pattern $\boldsymbol{x}_t$; a_t, Input atttribute in instant t; B, Inert gas used in TEP; $B1$, State of broken instrument with readings on top scale (200 °C); $B2$, State of broken instrument with binary oscillation of readings between 0° and 200 °C; $B3$, State of broken instrument with readings reduced for the background scale (0 °C); $B4$, State of partially broken instrument with readings oscillating around the normal operation value; $B5$, State of broken instrument with readings oscillating around values near 0 °C; $B6$, State of broken instrument with readings oscillating around values near 200 °C; *BM*, Bookmaker informedness; $C[I]$, Memory position accesssed by the vector of inputs I; *CN*, Condition negatives; *CP*, Condition positive; C_w, Confidence level of the WiSARD net for the recognition of a pattern w; $d_{a_{i,t}}$, Deviation attribute i in relation to the current input pattern $\boldsymbol{x}_t$; d, Terminal containing required output value; $D1$, $D2$, States with systematic deviations in relation to the normal operation value; *DOR*, Diagnostic odds ratio; E_h, Value of the series adjusted in period h; E_{h-1}, Value of the series adjusted in period h–1; F, Byproduct generated in TEP; $f(x)$, Function that defines approximately the limits for the classes considered; F_1, F1 score; F_j, Fault pattern type j; *FDR*, False discovery rate; *FN*, False negative; *FNR*, False negative rate; *FOR*, False omission rate; *FP*, False positive; *FPR*, False positive rate; G, H, Final products in TEP; h, Horizon of the processed time window; I, Vector of inputs for the RAM; k, Quantity of discriminators in the WiSARD net; $LR+$, Positive likelihood ratio; $LR-$, Negative likelihood ratio; *MCC*, Matthews correlation coefficient; *MK*, Markedness; n, Dimensionality of input vectors for the used application; N, State of normal sensor operation; $n_t(D_{hf})$, Training in the class discriminator with the highest number of patterns; *NA*, Total number of attributes used in the data set; *NC*, Number of classes; *NPV*, Negative predictive value; p, Input RAM node; p, Number of bits of the vector of inputs for the RAM; P, Prevalence; $P_{2,max}$, Second highest score obtained by one of the discriminators of the WiSARD net; P_{max}, Maximum score obtained by one of the discriminators of the WiSARD net; Pun_i, Punishment for the attribute i; *PPV*, Positive predictive value; q, Phase in which the RAM node is runing: learning or test; r, RAM number of a discriminator; Rec_i, Reward for the attribute i; $R_{i,c}$, Attribute position i in class c; RP_i, Reward and Punishment for the attribute i; *SPC*, Specificity; T, Total population; *TN*, True negative; *TNR*, True negative rate; *TP*, True positive; *TPR*, True positive rate; $V_{i,c}$, Value that represents the importance of the attribute i for class c; W, Adjustment coefficient belonging to the interval $0 < W < 1$; w, Input pattern for the weightless neural net; $\boldsymbol{x}$, Input pattern for the system; $\boldsymbol{x}_t$, Input pattern $\boldsymbol{x}$ in instant t; y, Output of the weightless neural net with value equal to a class label; β, Possible values for the conventional bleaching; $\Delta_{a_{i,t}}$, Pertinence degree of the attribute i for the input pattern $\boldsymbol{x}_t$; μ, Arithmetic mean of the t values of the processed time series; σ, Standard deviation of the t values of the processed time series.

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1. Introduction

Both current technological advances and the increasing demand for more productive and reliable industrial processes have resulted in more complex automation with greater data availability. As a result, there is an increasing need for more efficient supervision and control systems, especially for Fault Detection and Diagnosis (FDD) in dynamic environments. In a production system, a fault is an abnormal operating condition caused by factors such as design errors, installation errors, misuse or the effects of natural degradation. The availability of mechanisms for early and reliable detection of faults decreases the risks of malfunction or unscheduled shutdowns of the system. Consequently, it increases equipment reliability and avoids material losses, environmental accidents and harm to workers (Blázquez & Miguel, 2005; Chiang, Russel, & Braatz, 2001; Romano & Kinnaert, 2006; Yang & Liu, 1998).

Considering the *a priori* knowledge used for their development, FDD systems are designed using process models or historical data. Such approaches can be subdivided into quantitative and qualitative methods (Venkatasubramanian, Rengaswamy, & Kavuri, 2003; Venkatasubramanian, Rengaswamy, Yin, & Kavuri, 2003). Systems based on historical data can extract relevant features from the data in order to map the relationships and the existing limits between the considered classes or groups. In this group, some quantitative methods can be highlighted: statistical classifiers (Luo, Wang, & Cui, 2011; Ma, Wong, Jang, & Tseng, 2010; Soares & Galvão, 2010); neural networks (Lau, Ghosh, Hussain, & Hassan, 2013; Leite, Costa, & Gomide, 2012; Sartori, 2012; Zarei, 2012); fuzzy logic (Andrade, 2012; Andrade, Fontes, & Embiruçu, 2011; Lau et al., 2013; Leite, Costa, & Gomide, 2012; Li, Yu, Hilton, & Liu, 2013; Silva, Palhares, & Caminhas, 2012); Principal Component Analysis (PCA) (Barragan, Fontes, & Embiruçu, 2016; Jiang, Yan, & Zhao, 2013; Lau et al., 2013); method of partial least squares (Zhang, Zhou, Qin, & Chai, 2010); wavelet transforms (Barragan et al., 2016). Among the qualitative methods, expert systems (Saravanan, Cholairajan, & Ramachandran, 2009; Wang, Li, & Vrbanek, 2012; Zadeh, 2008) and qualitative trend analysis (Maurya, Rengaswamy, & Venkatasubramanian, 2007) are noteworthy. In the model-based approaches, the actual behavior of the monitored system is compared to the response obtained by a representative model of the process. The result of this supervised comparison is a residual vector used to detect the presence of faults. In this group the following quantitative methods can be highlighted: state and output observers (Chetouani, 2008; Kalman, 1960); parity space and equations (Beckerle, Schaede, Butzek, & Rinderknecht, 2012; Blesa, Jiménez, Rotondo, Nejjari, & Puig, 2014; Zakharov, Tikkala, & Jämsä-Jounela, 2013; Zhong, Song, & Ding, 2015); extended Kalman filter (Kalman, 1960; Patwardhan & Shah, 2006); support vector machine (Zhang, Zhou, Guo, Zou, & Huang, 2012; Deng, Lin, & Chang, 2011; Duan, Xie, Bai, & Wang, 2016; Park, Kwon, Kim, & Baek, 2011); and parameter identification and estimation methods (Johansson, Bask, & Norlander, 2006; Pouliezos, Stavrakakis, & Lefas, 1989). In the qualitative approach, the following methods stand out: fault trees (Nguyen & Lee, 2008; Simões Filho, 2006); qualitative simulation (Berleant, 1991); qualitative process theory (Venkatasubramanian, Rengaswamy, & Kavuri, 2003); and Bayesian networks and other Bayesian reasoning extensions, such as signed directed graphs and evidence theory (Ji, Xia, & Meng, 2015; Luo, Yang, Hu, & Hu, 2012; Xiao, Zhao, Wen, & Wang, 2014). Serdio, Lughofer, Pichler, Buchegger, and Efendic (2014, 2015) have developed approaches that combine historical data, automatic model extraction and residual generation, which seem useful for fault detection and isolation with abrupt and incipient faults.

Many studies have shown the positive advantages of statistically based and artificial intelligence based techniques for solving FDD problems, especially hybrid systems involving fuzzy logic, genetic algorithms and mainly neural networks (Chen & Chen, 2011; Ghate & Dudul, 2010; Mendonça, Sousa, & Sá da Costa, 2009; Niaki & Abbasi, 2005; Sartori, Amaro, Souza Júnior, & Embiruçu, 2012; Sharma, Dewan, & Chatterji, 2015; White & Lakany, 2008; Wu, 2011; Zarei, 2012). The noise tolerance shown by artificial neural networks (Özyurt & Kandel, 1996) and the ability of fuzzy logic to deal with information inaccuracies, ambiguities and uncertainties (Leite et al., 2012) mean that neuro-fuzzy hybrid systems are widely used (Hell, Costa, & Gomide, 2008; Lau et al., 2013). These techniques are well suited to non-linear systems because they do not require explicit mathematical models (Angelov & Yager, 2012; Bartyś, Patton, Syfert, de las Heras, & Quevedo, 2006; Bocaniala & da Costa, 2006; Li et al., 2013; Lo, Fung, & Wong, 2009; Ma et al., 2010; Rigatos & Zhang, 2009). According to Sartori, Amaro, Arduini, Souza Júnior, and Embiruçu (2016), most applications of FDD systems are in power generating and distribution units, pieces of equipment in process industries (reactors, columns, sensors and actuators) and motors and bearings. This study lists neural networks, fuzzy logic, principal component analysis, Kalman filter, support vector machines, genetic algorithms and expert systems as the most commonly used techniques in descending order.

In general, such approaches are well suited to the detection and diagnosis of abrupt faults. In the context of incipient faults in dynamical systems, the FDD problem is more complex and the studies and research found in the literature have yet to find appropriate solutions for problems such as: multivariate problems and a diversity in the number of classes; nonlinear processes with incipient faults present in two or more considered classes; difficulty in obtaining historical data with real-world applications. The main contribution of this paper is to propose a detection and diagnosis system for incipient faults in dynamic systems, without the need to use a mathematical model or residual calculations and with a low false alarm rate. The proposed system is based on Weightless Neural Networks [WNN, an acronysm also used for Wavelet Neural Networks (Lei, He, & Zi, 2011)], initially proposed by Aleksander (1967). WNN are digital models based on Random Access Memory (RAM) devices. Unlike conventional neural models, learning happens in memories inserted into the neuron, in the form of truth tables. Compared to weighted models, WNN have the advantages of a diversity of use of these memories, such as similarity with the conventional digital systems; fast and flexible learning algorithms; accuracy and consistency in the results, no need for generating residuals and network retraining; and above all, great potential for pattern recognition and classification.

The applications of WNN for pattern recognition and classification problems can be found in several areas, including: digit and fingerprint recognition (Bandeira, França, & França, 2009; Conti, Militello, Vitabile, & Sorbello, 2009; Grieco, Lima, De Gregorio, & França, 2010); faces and facial features recognition (Araújo, 2011; Sirlantzis, Howells, & Gherman, 2009; Subhashini & Nagarajan, 2014); robot navigation (McElroy & Howells, 2011; Nurmaini, Hashim, & Jawawi, 2009); data stream clustering (Cardoso, Lima, de Gregório, Gama, & França, 2011); and time series forecasting (De Souza, Freitas, & De Almeida, 2010; Mpofu, 2006). However, no work addressing the problems of FDD with the use of WNN was found in the literature. The papers presented by De Gregorio and Giordano (2014) and Cardoso, De Gregorio, Lima, Gama, and França (2012) approach this context, but do not deal with FDD problems. De Gregorio and Giordano (2014) used WNN for the problem of detecting changes in the vision field of a camera. The proposed system, called CwisarDH, uses a discriminator for each coverage point of the video with the color concept. Cardoso et al. (2012) presented the StreamWiSARD system for flow data grouping with sliding-window. The system consists of WiSARD discriminators as primary units and is able to define high quality clusters, restricted to a small number of microclusters. The absence of