Fault Detection and Diagnosis of Distributed Parameter Systems Based on Sensor Networks and Artificial Intelligence

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Abstract: - This paper presents some approaches on the new applications in fault estimation, detection and diagnosis emerged from three powerful concepts: theory of distributed parameter systems, applied to large and complex physical processes, artificial intelligence, with its tool adaptive-network-based fuzzy inference and the intelligent wireless ad-hoc sensor networks. Sensor networks have large and successful applications in the real world. They may be placed in the areas of distributed parameter systems, to be seen as a "distributed measuring sensor" for the physical variables. Using sensor networks multivariable estimation techniques may be applied in distributed parameter systems. Fault detection and diagnosis in distributed parameter systems become more easily and more performing using these concepts. The paper presents some applications in fault detection and diagnosis based on the adaptive-network-based fuzzy inference, allows treatment of large and complex systems with many variables by learning and extrapolation.

Key-Words: - Fault detection and diagnosis, wireless sensor networks, non-linear system identification, distributed parameter systems, adaptive-network-based fuzzy inference, multivariable estimation techniques, auto-regression, heat distribution, partial differential equations.

1 Introduction

The supervision, fault detection and fault diagnosis are important to improve reliability, safety and efficiency in maintenance of industrial processes, seen like lump parameter systems. In the last decades these methods were applied with success in electrical drives, power plants, aircrafts or chemical plants. The classical approaches in the field of fault detection and diagnosis are using analytical methods [1] of system identification based on linear models as: parameter estimation, state space observers and parity equations. For non-linear systems identification usage of the artificial intelligence concepts as fuzzy logic, neural networks and the adaptive-network-based fuzzy inference [2] represents powerful tools in system identification. The distributed parameter systems are in practice more complex processes, described using partial differential equations, such as the propagation of sound or heat, electrostatic phenomena, fluid flows, elasticity. Processes considered with variables distributed in space may be watched using modern wireless intelligent sensor networks [3, 4]. The commercial sensor networks have sensors for all kind of variables from physical distributed parameters systems as: temperature, pressure, radiation, light intensity, acceleration and other. Some classical methods are developed for identification of the general distributed parameter system identification [5, 6]. Recent approaches in the above field are reported in [7, 8]. The author has developed and published several theories related of using multivariable estimation techniques based on artificial intelligence for the identification of distributed parameter systems [9, 10, 11], in the new context of intelligent sensor networks as a "distributed sensor". As a distributed tool they may be used to measure time variables in the complex distributed parameter systems. In this application, with a large field of interest in science and engineering, all the above topics contribute, converging to the same objective – identification, detection and diagnosis of fault in distributed parameter systems. The paper presents a general theory, with 2 estimation algorithms and a general method for fault detection and diagnosis based on those estimation algorithms.

2 Mathematical Models

A distributed parameter system has a general mathematical model in continuous time as a partial differential equation, as an example for a parabolic case, as:

$$f\left(\frac{\partial\theta}{\partial t}, \frac{\partial\theta}{\partial\zeta}, \frac{\partial^2\theta}{\partial\zeta^2}, ...\right) = 0 \qquad (1)$$

with variables $\theta(\zeta, t)$, depending on time t and on space ζ, where ζ is x for one axis, (x, y) for two axis or (x, y, z) for three axis.

In the practical application case studies limits and initial conditions of the equation (1) are imposed:

$$\theta(0,t) = \theta_{\zeta 0},\ t\in[0,T], \theta(\zeta,0) = 0,\ \zeta\in[0,l], \qquad (2)$$
$$\theta(l,t) = \theta_{\zeta l},\ t\in[0,T]$$

Boundary conditions for the equation (2) are: when the variable value the boundary is specified we are speaking about Dirichlet conditions and when the variable flux and transfer coefficient are specified there are Neumann conditions.

A system with finite differences may be associated to the equation (1). For this purpose the space S is divided into small pieces of dimension l_p:

$$l_p = l / n \qquad (3)$$

In each small piece S_{pi}, i=1,…,n of the space S the variable θ could be measured at each moment t_k, using a sensor from the sensor network, in a characteristic point $P_i(\zeta_i)$, of coordinate ζ_i. Let it be θ_i^k the variable value in the point $P_i(\zeta_i)$ at the moment t_k. It is a general known method to approximate the derivatives of a variable with small variations. In the equation with partial derivatives there are derivatives of first order, in time, and derivatives of first and second order in space. So, theoretically, we may approximate the variable derivative in time with a small variation in time, with the following relation:

$$\frac{\partial\theta}{\partial t} = \frac{\theta_i^{k+1} - \theta_i^k}{t_{k+1} - t_k} \qquad (4)$$

The first and the second derivatives in space may be approximated with small variations in space to obtain the following relations:

$$\frac{\partial\theta}{\partial x} = \frac{\theta_i^k - \theta_{i-1}^k}{l_p},\ \frac{\partial^2\theta}{\partial x^2} = \frac{\theta_{i+1}^k - 2\theta_i^k + \theta_{i\_1}^k}{l_p^2} \qquad (5)$$

We may consider the variable is measured as samples at equal time intervals with the value:

$$h = t_{k+1} - t_k \qquad (6)$$

called sample period, in a sampling procedure, with a digital equipment. Combining the equations (4, 5, 6) in the equation (1) a system with differences results:

$$f(\theta_i^k, \theta_{i-1}^k, \theta_i^{k+1}, \theta_{i-1}^{k+1}) = 0 \qquad (7)$$

Taking account of equation (7) is obvious that two estimation algorithms may be developed as follows. We may use several estimation algorithms based on discrete models of the partial derivative equation.

Estimation algorithm 1. It estimates the value of the variable θ_i^{k+1} at the moment t_{k+1}, measuring the values of the variables $\theta_{i-1}^k, \theta_{i+1}^k, \theta_i^k$ at the anterior moment t_k:

$$\theta_i^{k+1} = f_1\left(\theta_{i-1}^k, \theta_{i+1}^k, \theta_i^k\right) \qquad (8)$$

This is a multivariable estimation algorithm, based on the adjacent nodes [9].

Estimation algorithm 2. It estimates the value of the variable θ_i^{k+1} at the moment t_{k+1}, measuring the values of the same variable $\theta_i^k, \theta_i^{k-1}, \theta_i^{k-2}, \theta_i^{k-3}$, but at four anterior moments t_k, t_{k-1}, t_{k-2} and t_{k-3}.

$$\theta_i^{k+1} = f_2\left(\theta_i^k, \theta_i^{k-1}, \theta_i^{k-2}, \theta_i^{k-3}\right) \qquad (9)$$

This is an autoregressive algorithm.

Estimator model. The estimator is a non-linear one, described by the function $y=f(u_1, u_2, u_3, u_4)$, using the adaptive-network-based fuzzy inference [2, 10]. Its general structure is presented in Fig. 1.

It has four inputs u_1, u_2, u_3 and u_4 and one output y. The ANFIS procedure may use a hybrid learning algorithm to identify the membership function parameters of single-output, Sugeno type fuzzy inference system. A combination of least-squares and backpropagation gradient descent methods may be used for training membership function parameters, modeling a given set of input/output data.

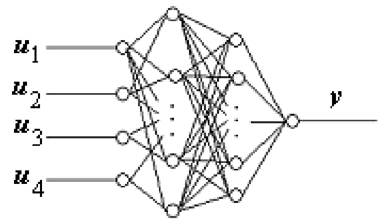

Fig. 1. The estimator input-output general structure

In the inference method *and* may be implemented with product or minimum, *or* with maximum or summation, implication with product or minimum and aggregation with maximum or arithmetic media. The first layer is the input layer. The second layer represents the input membership or fuzzification layer. The neurons represent fuzzy sets used in the antecedents of fuzzy rules determine the membership degree of the input. The activation function represents the membership functions. The 3rd layer represents the fuzzy rule base layer. Each neuron corresponds to a single fuzzy rule from the rule base. The inference is in this case the sum-prod inference method, the conjunction of the rule antecedents being made with product. The weights of the 3rd and 4th layers are the normalized degree of confidence of the corresponding fuzzy rules. These weights are obtained by training in the learning process. The 4th layer represents the output membership function. The activation function is the output membership function. The 5th layer represents the defuzzification layer, with single output, and the defuzzification method may be the centre of gravity.

3 Sensor network capabilities

A Crossbow sensor network was used in practice. It has the following components: a starter kit, a MICA2 2,4 GHz wireless module, and an MTS320 sensor board. Their nodes are 2 MICAz 2,4 GHz modules, with 2 sensors MTS400, which are measuring temperature, humidity, pressure, ambient light intensity; 1 MICAz 2,4 GHz with 2 sensors MTS310 and 1 module MICAz 2,4 GHz working as a central node when it is connected through the UB port. A gateway MIB520 for node programming and a data acquisition board MDA320 with 8 analogue channels are provided. The network has the following software: MoteView for history sensor network monitorization and real time graphics and MoteWorks for nod programming in MesC language. The user interface allows some facilities, as: administration, searching, connections options and so on.

This modern wireless sensor network has multiple measuring capabilities. So, it can measure temperature, humidity, light intensity or acceleration on 2 axes. For these kind of physical variables the mathematical models are as follows.

For temperature:

$$\frac{\partial\theta}{\partial t} = a\left(\frac{\partial^2\theta}{\partial x^2} + \frac{\partial^2\theta}{\partial y^2}\right) + Q(x,y,t) \tag{10}$$

where Q is the time variable source of heating,positioned in space and θ is the temperature.

For light intensity:

$$E(x) = \frac{I}{h^2 + x^2},\ E = \frac{\Delta\Phi}{\Delta S},\ \Delta\Phi = I\frac{\Delta S}{r^2} = I.\Delta\alpha \tag{11}$$

where I is the luminous intensity of the light source, at the distance x and high h, as a measure of the source intensity as seen by the eye, E is the luminance at the specific point, defined as a ratio, with $\Delta\Phi$ representing the flux that strikes a tiny area ΔS, calculated considering a spherical surface of radius r, with $\Delta\alpha$ representing the solid angle.

For acceleration:

$$a_x = \frac{dv_x}{dt},\ a_y = \frac{dv_y}{dt}, v_x = \frac{dx}{dt},\ v_y = \frac{dy}{dt} \tag{12}$$

where the above notations represents the acceleration a_x, a_y, the speed v_x, v_y and the space x, y on two axis for an object of the mass m, under a force F. Some characteristics measured for the sensor network are presented in Fig. 2.

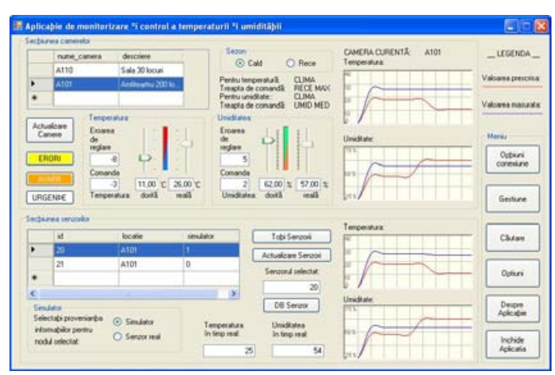

Fig. 2. Temperature am humidity transient characteristics measured with the sensor network

A sensor network is made by hhundred or thousands of ad-hoc tiny sensor nodes spread across the space S. Sensor nodes collaborate among themselves, and the sensor network provides information anytime, by collecting, processing, analysing and disseminating temperature measured data. Sensor network is working as a distributed sensor. The constructive and functional representation of a sensor network is presented in Fig. 3.

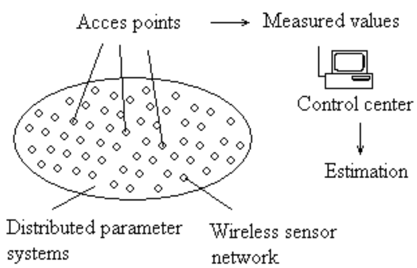

Fig. 3. A sensor network with mobile access

The sensor networks have different structures, as the star networks (point-to-point), which are networks in which all sensors are transmitting directly with a central data collection point. New nodes automatically are detected and incorporated. The number and the place point of the de sensor nodes may be discussed according to the desired accuracy of estimation [10, 11] using different identification methods.

4 Estimation and Detection Structure

The present paper considers two multivariable estimation models, one as regressive (8) and the second as an autoregressive (9), both based on nonlinear ANFIS estimator, which can efficiently approximate the time evolution in space of the measured values provided by each and every sensor within the coverage area. An estimation model describes the evolution of a variable measured over the same sample period as a non-linear function of past evolutions. This kind of systems evolves due to its “non-linear memory", generating internal dynamics. The estimation model definition is:

$$y(t) = f(u_1(t),...,u_n(t)) \quad (13)$$

where u(t) is a vector of the series under investigation (in our case is the series of values measured by the sensors from the network):

$$u = [u_1 \quad u_2 \quad ... \quad u_n]^T \quad (14)$$

and f is the non-linear estimation function of non-linear regression, n is the order of the regression. By convention all the components $u_1(t),\ldots,u_n(t)$ of the multivariable time series u(t) are assumed to be zero mean. The function f may be estimated in case that the time series u(t), u(t-1),…, u(t-n) is known (recursive parameter estimation), either predict future value in case that the function f and past values u(t-1),…, u(t-n) are known (AR prediction). The method uses the time series of measured data provided by each sensor and relies on an (auto)-regressive multivariable predictor placed in base stations as it is presented in Fig. 4.

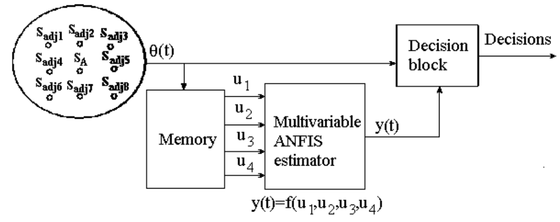

Fig. 4. Estimation and detection structure

The principle is the following: the sensor nodes will be identified by comparing their output values $\theta(t)$ with the values $y(t)$ predicted using past/present values provided by the same sensors or adjacent sensors (*adj*). After this initialization, at every instant time t the estimated values are computed relying only on past values $\theta_A(t-1)$, …, $\theta_A(0)$ and both parameter estimation and prediction are used as in the following steps. First the parameters of the function f are estimated using training from measured values with a training algorithm as backpropagation for example. After that, the present values $\theta_A(t)$ measured by the sensor nodes may be compared with their estimated values $y(t)$ by computing the errors:

$$e_A(t) = |\theta_A(t) - y(t)| \quad (15)$$

If these errors are higher than the thresholds ε_A at the sensor measuring point a fault occurs. Here, based on a database containing the known models, on a knowledge-based system we may see the case as a multi-agent system, which can do critics, learning and changes, taking decision based on node analysis from network topology. Two parameters can influence the decision: the type of data measured by sensors and the computing limitations. Because both of them are a priori known an off-line methodology is proposed. Realistic values are between 3 and 6.We are choosing 4 as in equations (8) and (9). So, the method for fault detection and diagnosis provided by this paper may be synthesised as follows:

The method recommended for fault detection and diagnosis based on identification, sensor network and ANFIS. -Placing a sensor network in the field of the distributed parameter system. -Acquiring data, in time, from the sensor nodes, for the system variables. -Using measured data to determine an estimation model based on ANFIS. -Using measured data to estimate the future values of the system variables. -Imposing an error threshold for the system variables. -Comparing the measured data with the estimated values. -If the determined error is greater then the threshold a default occurs. -Diagnosing the default, based on estimated data, determining its place in the sensor network and in the distribute parameter system field.

5 Case Study

In this paper a case study consisting in a heat distribution flux through a plane square surface of dimensions l=1, with Dirichlet boundary conditions as constant temperature on three margins:

$$h_\theta \theta = r \tag{16}$$

with r=0, and a Neuman boundary condition as a flux temperature from a source

$$nk\nabla\theta + q\theta = g \tag{17}$$

where q is the heat transfer coefficient q=0, g=0, h_θ=1.

The heat equation, of a parabolic type, is:

$$\rho C \frac{\partial \theta}{\partial t} = \nabla(k\nabla\theta) + Q + h_\theta(\theta_{ext} \_ \theta) \tag{18}$$

where ρ is the density of the medium, C is the thermal (heat) capacity, k is the thermal conductivity, coefficient of heat conduction, Q is the heat source, h_θ is the convective heat transfer coefficient, θ_{ext} is the external temperature. Relative values are chosen for the equation parameters: ρC=1, Q=10, k=1.

With the above conditions the equation may be solved using the finite element method. The optimize mean meshes and nodes are presenting in Fig. 5.

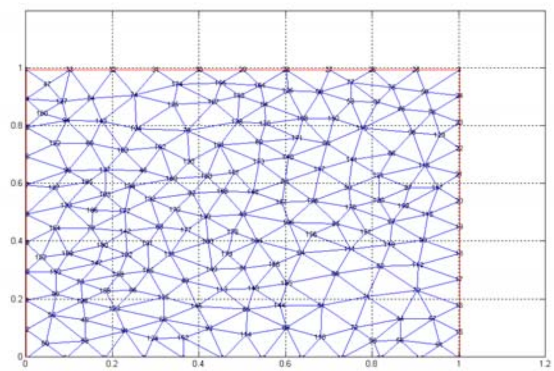

Fig. 5. The optimize meshes and nodes

The temperature represented height 3D over the surface analyzed is presented in Fig. 6.

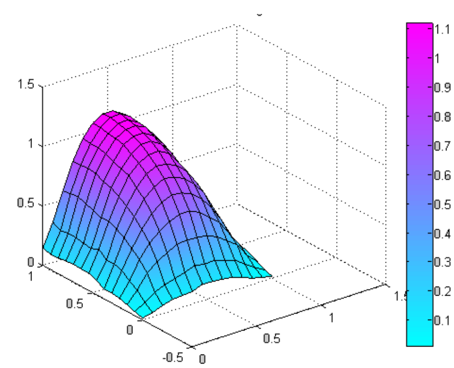

Fig. 6. The temperature over the plane

In practice we are using a reduced number of sensors, which is equivalent to a number reduced of nodes and meshes, for example a sensor network with only 13 nodes, placed like in Fig. 7.

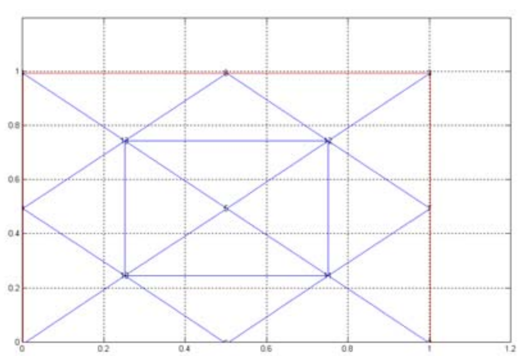

Fig. 7. Sensor network position in the field

For this case the solution with the finite element method is represented in Fig. 8.

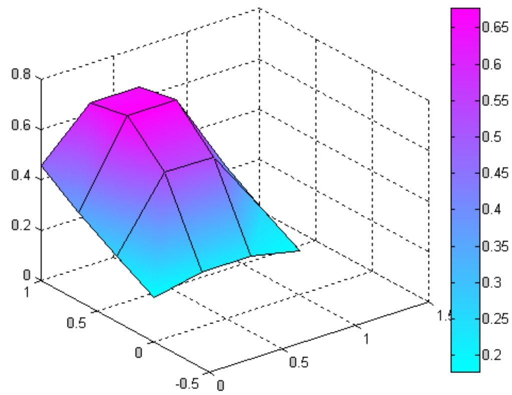

Fig. 8. Solution for 13 nodes

The repartition of temperature on isotherms in plane is presented in Fig. 9.

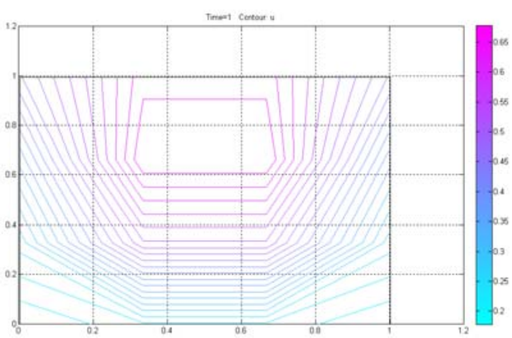

Fig. 9. Temperature in plane

In the application we are choosing the nodes 8, 13, 12 5 and 11 from the Fig. 7 to apply the estimation method. The transient characteristics of the temperature are presented in Fig. 10 for 101 samples.

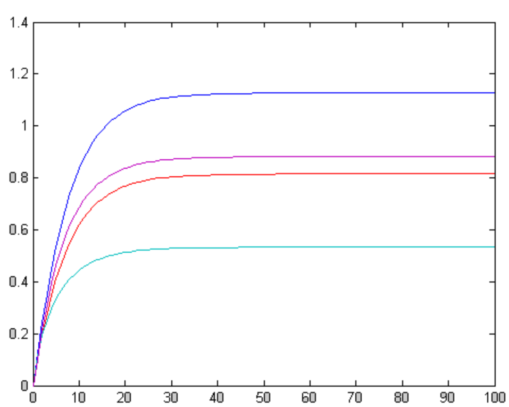

Fig.10. Temperature transient characteristics

The time period was 1 and the sampling period was 0,01. In Fig. 10 the temperature for nodes 13 and 12 are the same, because they are on the same isotherm.

We are chosen as an example the node 5 to be the node with the estimated temperature, based on the first recursive algorithm:

$$\theta_5^{k+1} = f(\theta_8^k, \theta_{13}^k, \theta_{12}^k, \theta_{11}^k) \tag{19}$$

And also for the node 5 we will apply the second algorithm, auto-recursive:

$$\theta_5^{k+1} = f(\theta_5^k, \theta_5^{k\text{-}1}, \theta_5^{k\text{-}2}, \theta_5^{k\text{-}3}) \tag{20}$$

The fuzzy inference system structure is presented in Fig. 11.

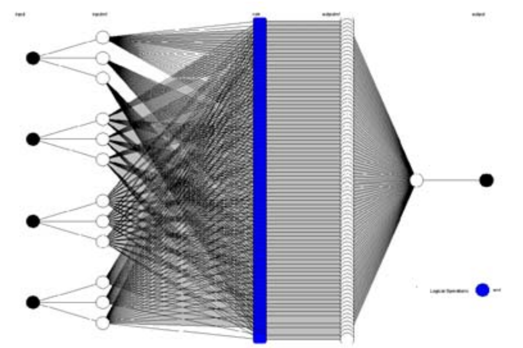

Fig. 11. FIS structure

The comparison transient characteristics for training and testing output data are presented in Fig. 12.

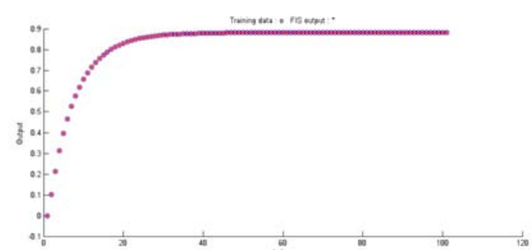

Fig. 12. Comparison between training and testing output

The average testing error is $2{,}017.10^{-5}$. Number of training epochs is 3.

For the second algorithm the training error was of 0,007, number of epochs 3 and the testing error 0,007.

The FIS general structure is the same, but with different parameter values.

The estimated output for the second algorithm is presented in Fig. 13.

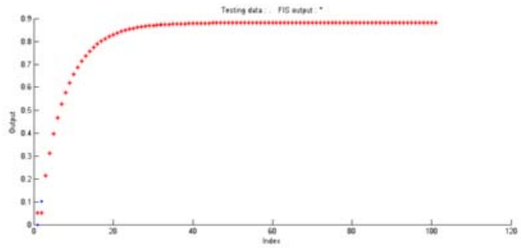

Fig. 13. The estimated output for the second algorithm

Comparing the two algorithms the first one had a better testing error.

If a default appears at the sensor 5 an error occurs in estimation, like in Fig. 14.

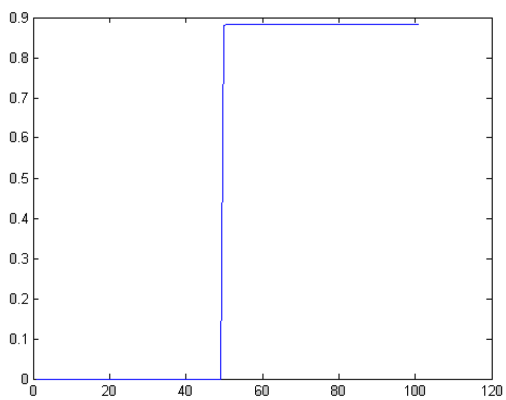

Fig. 14. Error at the fifth node for a fault in the network

Detection of this error is equivalent to a default at sensor 5, from other point of view in the place of the senor 5 in the space of the distributed parameter systems and in heat flow around the sensor 5.

6 Conclusion

The paper presents two algorithms and a method for fault detection and diagnosis of distributed parameter systems, with the adaptive network based fuzzy inference systems and the intelligent wireless sensor networks. The sensor network is seen as a distributed sensor. The algorithms are one based on regression using the values provided by the adjacent nodes of the sensor network and the second is an autoregressive one based on the values from anterior time moments of the same node. The method described the way how to use all these concepts for fault detection and diagnosis in distributed parameter systems, using the measured values provide by the sensor and the estimated values computed by the ANFIS estimator, calculating an error and detecting the fault based on a decision taken after a threshold comparison. Estimations methods may be applied in the case of discovery of malicious nodes in wireless sensor networks. A case study for the both algorithms is presented for heat transfer in plane. A comparison between the two algorithms is made. Good approximations were obtained. Developing of the algorithms and the method are taken in consideration in the future, in other applications, considering all the capabilities of the sensor nodes to measure physical variables. This approach allows treatment of large and complex systems with many variables by learning and extrapolation.

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References:

[1] R. Isermann, Supervision, fault-detection and fault diagnosis methods. An introduction. *Control Eng. Practice*, Vol. 5, No. 5, 1997, p. 639-652.

[2] J. S. Roger Jang, ANFIS: Adaptive Network Based Fuzzy Inference Systems, *IEEE Trans. on Systems, Man, and Cybernetics*, Vol. 23, No. 03, p. 665-685, May 1993.

[3] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, Wireless Sensor Networks: A Survey. *Computer Networks*, 38(4), March, 2002.

[4] M. Tubaishat, S. Madria, Sensor networks: an overview, *IEEE Potential*, Apr. 2003, Vol. 22, Issue 2, p. 20-23.

[5] C.S. Kubrulsky, M.R. de S. Vincente, Distributed parameter system identification. A survey, *International Journal of Control*, Volume 26, Issue 4 Oct. 1977, p. 509 – 535.

[6] D. Ucinski, *Optimal Measurement Methods for Distributed Parameter System Identification*, CRC Press, 2004.

[7] H. Wang, P. Chen, Fault Diagnosis for a Rolling Bearing used in a Reciprocating Machine by Adaptive Filtering Technique and Fuzzy Neural Network, *WSEAS Transactions on Systems*, Issue 1, Volume 7, January 2008, p. 1-6.

[8] S. Postalcioglu, K. Erkan, E. D. Bolat, Intelligent sensor fault detection and identification for temperature control, *Proc. of the 11th WSEAS Int. Conf. on Computers*, Greece, 2007, p. 131-134.

[9] C. Volosencu, Identification of Distributed Parameter Systems, Based on Sensor Networks and Artificial Intelligence, *WSEAS Transactions on Systems*, Issue 6, Vol. 7, June 2008, p. 785-801.

[10] C. Volosencu, D. I. Curiac, A Comparative Study for Identification of Distributed Parameter Systems using Sensor Networks and Adaptive-Network-Based Fuzzy Inference, *Proc. of the 11th WSEAS Int. Conf. on Automatic Control, Modeling and Simulation, ACMOS'09*, Istanbul, 2009, p. 386-394.

[11] C. Volosencu, Identification of Distributed Parameter Systems Based on Sensor Networks and Multivariable Estimation Techniques, *Proc. of the 9th WSEAS Int. Conf. on Simulation, Modeling and Optimization, SMO'09*, Budapest, Hungary, 2009, p. 187-196.