Identification of Distributed Parameter Systems, Based on Sensor Networks and Artificial Intelligence

CONSTANTIN VOLOSENCU
Departamentul de Automatica si Informatica Aplicata
Universitatea “Politehnica” University din Timisoara
Bd. V. Parvan Nr. 2, 300223, Timisoara
ROMANIA
constantin.volosencu@aut.upt.ro http://www.aut.upt.ro/~cvolos/

Abstract: - The paper presents a short survey of three topics: modern sensor networks, distributed parameter systems and estimation techniques, especially using artificial intelligence tools, to be involved in the new domain of identification of distributed parameter systems, based on sensor networks and artificial intelligence. As smart and small devices the modern sensors are capable to be implemented in large distributed parameter systems. Sensor networks, with hundred and thousands of ad-hoc tiny sensor nodes spread across a geographical, are acting as a distributed sensor in a distributed parameter system. Sensor network topics, sensor network architectures and sensor network applications are presented. Examples of distributed parameter systems with large application in practice as the process of heat conduction, applications related to electricity domain, motion of fluids, the processes of cooling and drying, phenomenon of diffusion and other applications are presented. The identification techniques are useful for applications ranging from control systems, fault detection and diagnosis, signal processing to time-series analysis. Methods to estimate linear back box models and models of artificial intelligence, as fuzzy logic and neural network are presented. The artificial intelligence tools may be used for identification of nonlinear complex systems as the distributed parameter systems are. A case study of malicious nod detection based on a neural autoregression method in the process of plane heat propagation is developed.

Keywords: - Wireless sensor networks, system identification, distributed parameter systems, neural networks.

1 Introduction

The development of wireless sensor allows development of new methods and algorithms for identification of systems, especially in the case of distributed parameter systems. The main principles consists in the fact that in this kind of identification the sensor network may be seen as a “distributed sensor” placed into a field, which is distributed parameter system, allowing measurement in well-chosen points of an infinite variable system. In the last years a lot of papers were published in the fields of identification of distributed parameter systems in sensor networks [1÷6]. This paper presents a short synthesis of the main aspects of the concepts involved in identification of distributed parameter systems based on sensor networks and artificial intelligence tools as fuzzy logic and neural networks.

Advances in scientific computation and developments in spatial sensor technology have enhanced the ability to develop modeling strategies and experimental techniques for the study of the spatiotemporal response of distributed nonlinear systems. The simplifying methods for modeling of these systems, that are trying to capture the distributed system dynamics through lumped parameter models, can be developed. Robust implementations of distributed system identification algorithms based on detailed space and time experimental data have now an important role to play [7÷12].

Advances in hardware and wireless network technologies have created smart, low-cost, low-power, multifunctional miniature sensor devices. These devices make up hundreds or thousands of ad hoc tiny sensor nodes spread across a geographical area. These sensor nodes collaborate among themselves to establish a smart sensing network. A sensor network can provide access to information anytime, anywhere by collecting, processing, analyzing and disseminating data. Thus, the network actively participates in creating a smart environment [13÷17].

…..Methods of artificial intelligence, as fuzzy logic and neural networks [18], can solve identification problems in multilinear complex systems with many variables, with unknown models.

Since for distributed parameter systems it is impossible to observe their states over the entire spatial domain, a possible solution is to locate discrete sensors to estimate the unknown system parameters as accurately as possible. There is recent original work on optimal sensor placement strategies for parameter identification in dynamic distributed systems modeled by partial differential equations. New development of new techniques and algorithms or adopting methods, which have been successful in the field of optimal control and optimum experimental design, are reported in papers.

In many sensor networks applications, sensors collect correlated measurements of a physical field, e.g., temperature field in a building or in a data center. However, the locations of the sensors are usually inconsistent with the application requirements. In the paper [2, 3] it is considered the problem of estimating the field at arbitrary positions of interest, where there are possibly no sensors, from the irregularly placed sensors. The sensor network on a graph is mapped, and by introducing the concepts of interconnection matrices, system digraphs, and cut point sets, real-time field estimation algorithms are derived. Simulations and real world experiments on temperature estimation are done.

A strategy by which sensor nodes detect and estimate non-localized phenomena such as boundaries and edges (e.g., temperature gradients, variations in illumination or contamination levels) is study in [4]. A general class of boundaries, with mild regularity assumptions, is considered, and theoretical bounds on the achievable performance of sensor network based boundary estimation are established. A hierarchical boundary estimation algorithm is proposed that achieves a near-optimal balance between mean-squared error and energy consumption.

Theory of partial differential equations is presented in [19] and applications to some systems with distributed parameters in [20, 21].

Developing low-order models of high fidelity is important if the objective is accurate control of the distributed parameter systems. The work [22] presents a method to develop a low-order models when there is no available exact model of the system. The foundations for this method, are singular value decomposition theory and the Karhunen-Loève expansion. It is shown that satisfactory closed-loop performance of the nonlinear distributed parameter systems can be obtained using a dynamic matrix controller designed using the finite order model.

In the paper [23] a methodology for the identification of distributed parameter systems, based on artificial neural network architectures, motivated by standard numerical discretization techniques used for the solution of partial differential equations is presented.

A new direct approach to identifying the parameters of distributed parameter systems from noise-corrupted data is introduced in [24]. The model of the system, which takes the form of a set of linear or nonlinear partial differential equations is assumed known with the exception of a set of constant parameters. Using finite-difference approximations of the spatial derivatives the original equation is transformed into a set of ordinary differential equations. The identification approach involves smoothing the measured data and estimating the temporal derivatives using a fixed interval smoother. A least-squares method is then employed to estimate the unknown parameters.

In the paper [25] the state-of-the-art algorithms for consensus-based distributed estimation using ad hoc wireless sensor networks, where sensors communicate over single-hop noisy links, is presented. Basic estimation criteria such as least-squares, maximum-likelihood and other are reformulated on a novel framework, amenable to distributed solutions. The framework encompasses adaptive filtering and smoothing of non-stationary signals through distributed LMS and Kalman filtering.

In the present paper three topics: modern sensor networks, theory of distributed parameter systems and theory of system identification, using especially artificial intelligence tools, are converged to a new domain – identification of distributed parameter systems, based on sensor networks and artificial intelligence (Fig. 1). A short survey of the main characteristics of these topics is made.

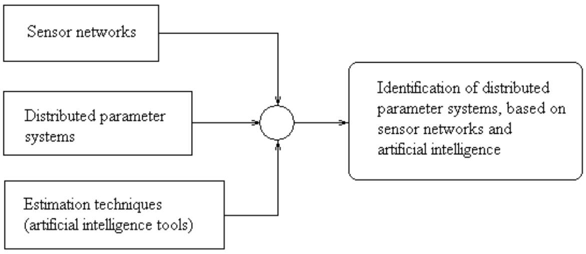

Fig. 1. Topics involving for modern identification

The second paragraph presents some principles and technical data of modern sensor networks. The third paragraph presents some examples of distributed parameter systems, with their mathematical models, on a large scale of applications, described with partial differential equations. The fourth paragraph presents some system identification basics, with linear and nonlinear models and artificial intelligence tools like fuzzy logic and neural networks. The fifth paragraph presents a study case of malicious node detection based on an autoregression neural model and a sensor network.

2 Sensor Networks

Wireless sensor networks are extremely distributed systems having a large number of independent and interconnected sensor nodes, with limited computational and communicative potential. The sensors are deployed for data acquisition purposes on a wide range of locations, sometimes in resource-limited and hostile environments such as disaster areas, seismic zones, ecological contamination sites, military combat zones. In this structure data processing is at the sensor level, data transmission is wireless, sensing mechanism is not necessarily power supply is not necessarily wireless.

Sensor network applications include: environmental monitoring, civil infrastructure monitoring, shared resource utilization, tracking, perimeter protection [26] and military surveillance. Application are in micro-climates, air quality, soil moisture, animal tracking, energy usage, office comfort, wireless thermostats, wireless light switches. In techniques they have as applications data acquisition of physical and chemical properties, at various spatial and temporal scales, as in distributed parameter systems, for automatic identification, measurements over long period of time. The sensor networks are deployed for data acquisition purposes on a wide range of locations, in resource-limited and hostile environments such as disaster areas, seismic zones, ecological contamination sites, military combat zones. *All applications are distributed parameter systems*.

2.1 Modern Sensors

The modern sensors are smart, small, lightweight and portable devices, with a communication infrastructure intended to monitor and record specific parameters like temperature, humidity, pressure, wind direction and speed, illumination intensity, vibration intensity, sound intensity, power-line voltage, chemical concentrations and pollutant levels at diverse locations. The sensor number in a network is over hundreds or thousands of ad hoc tiny sensor nodes spread across different area. Thus, the network actively participates in creating a smart environment. They are low cost and low energy devices, realized in nanotechnology. With them we may developed low cost wireless platforms, including integrated radio and microprocessors. The sensors are adequate for autonomous operation in highly dynamic environments as distributed parameter systems. We may add sensors when they fail. They require distributed computation and communication protocols. They assure scalability, where the quality can be traded for system lifetime. They assure Internet connections via satellite.

The structure of a modern sensor is presented in Fig. 2 [13, 14, 15].

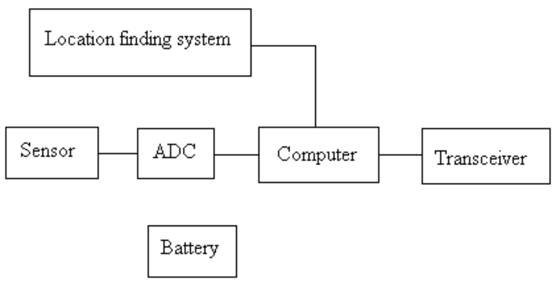

Fig. 2. The structure of a modern sensor

An example of a physical device is presented in Fig. 3.

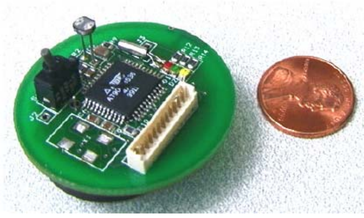

Fig. 3. A small sensor

We may see on integrated and discrete electronic devices, with the above mentioned functions, placed on a circuit. The dimension of a such sensor is comparable with a small coin.

The sensors are characterized by: a robust radio technology, cheap and energy efficient processors, lifetime energy source, on-board memory, flexible I/O for various sensors, common highly available components, efficient resource utilization – currently uses 10 μA average, high modularity, flexible open source platform. Some examples of technical data are: 128 KB instruction EEPROM, 4 KB data EEPROM, 512 KB External Flash Memory, radio with 38 K or 19 K baud, at 900MHz, LEDs, μP at 7,3 MHz, JTAG, programming board, ISM Bands: 433-434,8 MHz Europe, power consumption: 16 mA Tx, 9 mA Rx, 2 μA sleep, transmission range: 1m, off the floor 100m range, ground level 10 m range, interface block data to laptop, GPS, cost: $ 95.

Sensor are developed to measure: temperature, humidity, pressure, wind direction and speed, illumination intensity, vibration intensity, sound intensity, power-line voltage, chemical concentrations and pollutant levels at diverse locations and others. *All are variables in distributed parameter systems*.

2.2 Sensor Network Structure

Hundreds or thousands of ad-hoc tiny sensor nodes spread across a geographical area form the basis of a sensor network. Sensor nodes collaborate among themselves to establish a sensing network. The sensor network provides access to information anytime, anywhere, by collecting, processing, analyzing and disseminating data. The network actively participates in creating a smart environment. *Sensor network is working as a distributed sensor*.

The constructive and functional representation of a sensor network is presented in Fig. 4 [13, 14, 15].

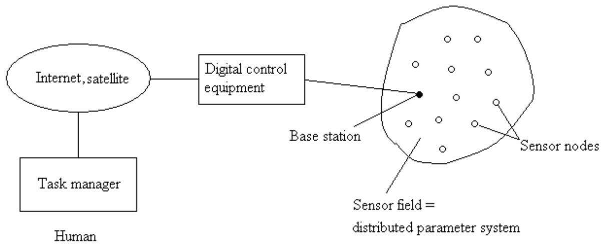

Fig. 4. Sensor network

The sensor networks have different *structures* [16]. The star networks (point-to-point), are networks in which all sensors are transmitting directly with a central data collection point. The mesh networks are networks in which sensors can communicate with each other. In mesh networks sensor nodes can relay messages from other sensor nodes, there is no need for repeaters. Software controls the flow of messages through network with self-configuration. New nodes automatically detected and incorporate. Advantages of the mesh structures are: robustness, easily deployed, no RF site surveys needed, no repeaters needed, easily expanded. Their disadvantages are: more complicated software, battery consumption of nodes increases, each node must transmit other nodes messages as well as its own, potentially less bandwidth. A sensor has the following hardware: radio node, antenna, on-board board microprocessor contains code for managing mesh network. As hardware development board it contains pins for sensor connection, microprocessor for handling signal, power supply, serial port, radio node plugs onto top of board. The sensor contains software on board for data acquisition, signal processing, embedded programming, embedded C language, messages format up to user.

In the field of sensors networks some topics are involved [27], like: development topics: deployment, localization, synchronization, calibration; wireless communication: wireless radio, characteristics, MAC protocols, link layer techniques, power control; sensor network architecture; networking topics: topology control, data gathering, network monitoring, network coding; data-centric: routing and aggregation, querying and data basis, storage; hardware; software; security. Standards and protocols are imposed for sensor networks development.

2.3 Sensor Network Architectures

Different structure may be uses in practice, for example [16]. The sensor network may be static or mobile. For a static case each sensor node knows its own location, even if they were deployed via aerial scattering or by physical installation. If not, the nodes can obtain their own location through the location process. Moreover, all the sensors passed a one-time authentication procedure done just after their deployment in the field. The sensor nodes are similar in their computational and communication capabilities and power resources to the current generation sensor nodes. Every node has space for storing up to hundreds of bytes of keying materials in order to secure the transfer of information through symmetric cryptography.

There is a base station into the network, sometimes called access point, acting as a controller and also as a key server. It is assumed to be a laptop class device and it is supplied with long-lasting power.

An example of a wireless cellular network architecture is presented in Fig. 5.

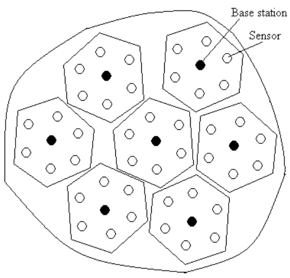

Fig. 5. Cellular network architecture

In this architecture, a number of base stations are already deployed within the field. Each base station forms a cell around itself that covers part of the area. Mobile wireless nodes and other appliances can communicate wirelessly, as long as they are within the area covered by one cell.

A versatile architecture is a sensor network with mobile access is presented in Fig. 6.

This structure used for large-scale sensor networks. The main difference related to the cellular network architecture is that base stations are considered to be mobile, so each cell has varying boundaries which implies that mobile wireless nodes and other appliances can communicate wirelessly, as long as they are at least within the area covered by the range of the mobile access point.

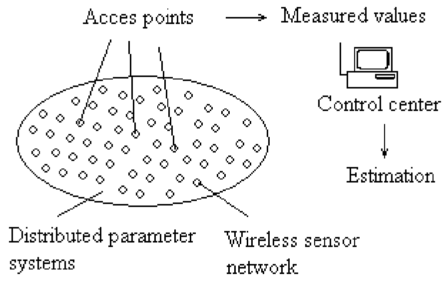

Fig. 6. A sensor network with mobile access

Multiple sensor nodes can detect an event situated in the surrounding area, so redundancy of sensor networks is assured.

In the next paragraph we presents some examples of such distribute parameter systems with their mathematical models with partial derivative equations.

3 Distributed Parameter Systems

The distributed parameter systems, opposed to the lumped parameter systems, are systems whose state space is infinite dimensional. An object whose state is heterogeneous has distributed parameters. Such a system is described by partial differential equations. Partial differential equations are used to formulate problems involving functions of several variables, such as the propagation of sound or heat, electrostatics, electrodynamics, fluid flow, elasticity. Distinct physical phenomena have identical mathematical formulations, and the same underlying dynamic governs them. Some examples of distributed parameter systems are presented as follow [19, 20, 21].

One of the most important domain of applications of the partial differential equations is the process of heat conduction, with propagation of heat in anisotropic medium: propagation of heat in a porous medium, transference of heat in semi-space compound by two materials submitted to heating, processes of transference of heat between a solid wall and a flow of hot gas, estimation of the temperature field in space with fissured zone having the form of a circular disc.

Applications related to electricity domain are: the propagation of electric current in cables, the heating of the electrical contacts.

In the field of motion of fluid there are: plane motion of viscous fluids, running of viscous fluids in rectilinear tube, computation of losses of nonstationary heat in subterranean pipe, running of gases in water main.

The processes of cooling and drying: cooling of clap, cooling of a sphere, drying of wood pieces, drying in vacuum.

…..Phenomenon of diffusion: diffusion flow in a heavy sphere for chemical reactions happening with finite speet on the sphere surface, the flames diffusion, which appears to the beginning of a tube, repartition density of particles loading by the meteorites.

…..Other applications are: estimation of the ice height covering the snow the arctic seas, motion of underground waters, alloy of heavy fusible particles, investigation of the wave close to the single point of the board of a plane plate, the growing of the gas particles in a fluid, substances combustion, the temperature modification in the air mass.

3.1 Process of Heat Conduction

Let it be an object of a volume $V \subset R^3$. The frontier of dominium V is a surface S, formed by a finite number of smooth surfaces. Let it be θ(P, t) the function of the object's temperature, at the time moment t, where $P \in V$ is a point in the volume V. If different points of object have different temperatures, θ(P, t)≠ct., then a heat transfer will take place, from the warmer parts to the less warm parts. Let it be a regular surface σ placed in V, which contains the point P. From the theory of thermal conductivity through the $d\sigma$ in the time dt a heat quantity dQ is passing, proportional to the product $d\sigma.dt$ and proportion to the function θ(P,t) derivative, along the normal n to the surface σ in the point P:

$$dQ = k\left|\frac{\partial \theta(P,t)}{\partial n}\right| dt d\sigma \tag{1}$$

where k is a proportionality factor, called coefficient of internal thermal conductivity of the object. The vector $grad$ θ has its direction along the normal at the level surface for θ=ct., in the sense of θ rising.

The law of heat propagation through an object in which there are no heat sources:

$$\gamma\rho\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x}\left(k\frac{\partial \theta}{\partial x}\right) + \frac{\partial}{\partial y}\left(k\frac{\partial \theta}{\partial y}\right) + \frac{\partial}{\partial z}\left(k\frac{\partial \theta}{\partial z}\right) \tag{2}$$

The heat sources in the object have a distribution given by the function:

$$F(t,P) = F(t,x,y,z) \tag{3}$$

If the object is homogenous $a = \sqrt{k/\gamma/\rho} = ct.$ and the equation (2) is written:

$$\frac{1}{a^2}\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x}\left(\frac{\partial \theta}{\partial x}\right) + \frac{\partial}{\partial y}\left(\frac{\partial \theta}{\partial y}\right) + \frac{\partial}{\partial z}\left(\frac{\partial \theta}{\partial z}\right) \tag{4}$$

In the case of heat propagation through a bar:

$$\gamma\rho\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x}\left(k\frac{\partial \theta}{\partial x}\right) + F(t,x) \tag{5}$$

The initial conditions or of the limit conditions have physical significance. The equation

$$\rho\gamma\frac{\partial \theta}{\partial t} = div(k\ grad\ \theta) + F(t,P) \tag{6}$$

does not determine completely the state of the object K. We must take in considerations the initial state of the object, the temperature distribution in the object at the moment t=0:

$$\theta(x,y,z,t)\big|_{t=0} = f(x,y,z) \tag{7}$$

called initial conditions.

3.2 Propagation of electric current in cables

Let it be a cable without margin at right. The potential in a point P(x) is V(x, t), where x is the distance from the cable origin and t is the time moment. The quantity of electricity on the unity distance dx is $C.V.dx$, where C is the capacity. If i is the current intensity, the electricity quantity which enter the element dx in the time dt is

$$\left[i - \left(i + \frac{\partial i}{\partial x} dx \right) dt \right] = -\frac{\partial i}{\partial x} dxdt \qquad (8)$$

and the rising of *C.V.dx* for a variation with *dt* of *t* corresponds to this:

$$C \frac{V(t+dt) - V(t)}{dt} dtdx = C \frac{\partial V}{\partial t} dtdx \qquad (9)$$

which is leading to the equality

$$\frac{\partial i}{\partial x} = -C \frac{\partial V}{\partial t} \qquad (10)$$

Using Ohm's law which gives $\frac{\partial V}{\partial x} = -Ri$ we obtains the equation

$$CR \frac{\partial V}{\partial t} = \frac{\partial^2 V}{\partial x^2} \qquad (11)$$

and with cR=1, we are led to the heat equation

$$\frac{\partial^2 V}{\partial x^2} - \frac{\partial V}{\partial x} = 0 \qquad (12)$$

In the above hypothesis the phenomenon of induction is neglected; if it is taken in consideration, the equation is

$$\frac{\partial^2 V}{\partial x^2} + 2 \frac{\partial V}{\partial t} = \frac{\partial^2 V}{\partial x^2} \qquad (13)$$

3.3 Heating of electrical contacts

The differential equation of conductor heating is

$$\frac{\partial^2 \theta}{\partial x^2} - \frac{\alpha l - \alpha_R \vartheta^2 A}{\lambda A} \theta + \frac{\rho_p}{\lambda} J^2 = 0 \qquad (14)$$

where λ is the thermal conductivity, α is the global transmitivity of heat at the conductor periphery, l is the conductor dimension, J is the current density, A is the transversal section of the conductor, θ is the conductor heating, with $\theta=\theta_m-\theta_r$ where θ_r is the conductor's temperature in normal functioning, θ_m is the maximum temperature in regime of short circuit, $\rho=\rho_p(1+\alpha_R\theta)$ is the material rezistivity.

3.4 Motion of fluid

For the plane motion of viscous fluids let consider an incompressible, viscous fluid of constant density ρ, in a plane movement. If (v_x, v_y) are the speed components in the point P(x, y) of the plane at the time moment t the movement equations are

$$\begin{aligned} \frac{\partial v_x}{\partial t} + v_x \frac{\partial v_x}{\partial x} + v_y \frac{\partial v_x}{\partial y} &= -\frac{1}{\rho} \frac{\partial p}{\partial x} + \nu \Delta v_x \\ \frac{\partial v_y}{\partial t} + v_x \frac{\partial v_y}{\partial x} + v_y \frac{\partial v_y}{\partial y} &= -\frac{1}{\rho} \frac{\partial p}{\partial y} + \nu \Delta v_y \end{aligned} \qquad (15)$$

where p is the pressure in this point, $\nu = \frac{\mu}{\rho}$, μ is the viscosity coefficient, and $\Delta = \frac{\partial^2}{\partial x^2} + \frac{\partial^2}{\partial y^2}$.

At the equations (16) the equations of continuity are added

$$\frac{\partial v_x}{\partial x} + \frac{\partial v_y}{\partial y} = 0 \qquad (16)$$

The current function is introduced

$$v_x = -\frac{\partial \varphi}{\partial y}, \quad v_y = -\frac{\partial \varphi}{\partial x} \qquad (17)$$

3.5 Running of viscous fluids in rectilinear tubes

Let be a rectilinear tube, which is leading a viscous liquid. The ax of tube is Oz. Let us consider the movement of a part of the liquid between two transversal sections z_1 and z_1+h. If A is the transversal section area supposed to be constant and ρ is the fluid density, the movement equation is

$$\rho A h \frac{\partial v}{\partial t} = A(p_1 - p_2) - R \qquad (18)$$

where p_1 and p_2 are the pressions in the two sections and R is the force on the tube wall. If v is the fluid speed in the direction of Oz axis, v is independent of

z if the liquid is incompressible

$$v = v(x, y, t) \tag{19}$$

The partial derivative equation is

$$\rho \frac{\partial v}{\partial t} = -\frac{\partial p}{\partial z} + \mu \left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} \right) \tag{20}$$

if the pression p is constant

$$\frac{1}{a} \frac{\partial v}{\partial t} = \left(\frac{\partial^2 v}{\partial x^2} + \frac{\partial^2 v}{\partial y^2} \right) \tag{21}$$

which it is the equation of heat propagation in plane, where $a=\mu/\rho$.

3.6 Losses of nonstationary heat in subterranean pipe

In the design and exploitation of oil and gas pipes a series of problems arise at the calculation of heat losses of pipes in conditions of a heat change nonstationary. For determining the nonstationary heat losses in the subterranean pipes the next equation is used

$$\frac{\partial \theta}{\partial t} = a \left[\frac{\partial^2 \theta_s}{\partial x^2} + \frac{\partial^2 \theta_s}{\partial y^2} \right] \tag{22}$$

where θ is the temperature of the transported material, θ_s is the soil temperature, t is the time, x, y are the Cartesians coordinates and a is a coefficient what is characterizing soil thermal diffusion.

3.7 Running of gases in water main

Suddenly in practice a great importance is to determine the necessary time to establish the pressure in a certainly point of a pipe after the valve closing. The nonstationary running of a gas is defined by the system

$$\frac{\partial p}{\partial x} = \rho \left(\frac{\partial v}{\partial t} + \frac{\lambda v^2}{2d} \right) \tag{23}$$

$$\frac{\partial \rho}{\partial t} = \frac{\partial (\rho v)}{\partial x}$$

where p is the pressure, v is the medium speed related at the section, d is the pipe diameter and λ is the friction coefficient.

3.8 Estimation of the ice height covering the snow on the arctic seas

A method used to determine the ice height of the arctic seas is the radiometry. Radiometry is based on registration of the heat radiation of which intensity varies with temperature and the radiation coefficient of the objects. The value of the radiations will characterize the relation between the ice height in its different stages. The temperature of the ice surface is determined from the heat equation, which describes the heat repartition in snow and ice

$$c_j \rho_j \frac{\partial \theta_j}{\partial t} = \lambda_j \frac{\partial^2 \theta}{\partial z^2}, \quad j = 1,2,3 \tag{24}$$

where c_j is the specific heat, ρ_j is the density, λ_j is the thermal conductivity coefficient, θ_j is the temperature, t is the time, z is the height coordinate. The indices j=1,2,3 correspond to the there medium: air, snow and ice. At the frontiers there are the conditions of equilibrium.

4 Identification Techniques

System identification is for building accurate, simplified models of complex systems from noisy time-series data. It provides tools for creating mathematical models of dynamic systems based on observed input/output data. The identification techniques are useful for applications ranging from control system design and signal processing to time-series analysis. Actually, there is a huge amount written on the subject of system identification. The textbooks [28÷31] deals with identification methods and also describes methods for physical modelling. For more details about the algorithms and theories of identification for distributed parameter systems there are [7÷12]. But only the experience with real data may help us to understand more. It is important to remember that any estimated model, no matter how good it looks on design, has only picked up a simple reflection of reality. So, in this aspect the sensor network is the powerful tool.

The identification techniques are useful for applications ranging from control systems, fault detection and diagnosis, signal processing to time-series analysis.

The structure of a modern control system is presented in Fig. 7 [32].

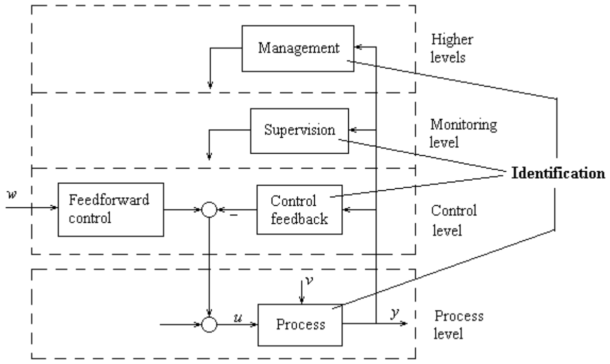

Fig. 7. The structure of a modern control system

It has the basic level of feedforward control, with control feedback, the second level with supervising, and the highest level of management. Identification finds its place in all these control levels.

There are identification methods based on parametric model and on nonparametric models. From the second category we enumerate spectral methods, correlations methods, recursive state estimation with Bayes filters and Gaussian filters.

Models describe relationships between measured signals.

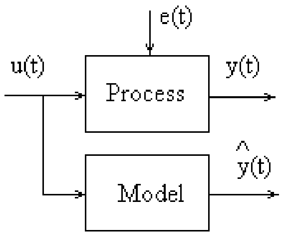

Fig. 8. The identification signals

The outputs y(t) are then partly determined by the inputs u(t). In most cases, the outputs are also affected by more signals than the measured inputs. Such unmeasured inputs are called disturbance signals or noise e(t). The relationship is y(t)=f(u(t), e(t)).

In case of systems that cannot be modeled based on physical insights it is possible to use standard models, which by experience are known to be able to handle a wide range of different system dynamics. A family of such ready made model, which tell the size and it is possible to find them to fit to measured data.

The estimation techniques are classified as follows: estimating parametric models, as estimating linear black-box models (with dynamics) like transfer functions and state-space models and estimating nonlinear black-box models. Estimation of linear black-box models is based on identification of polynomial and state-space models using various estimation algorithms: autoregressive models (ARX, ARMAX), Box-Jenkins (BJ) models, output-Error (OE) models, and state-space parameterizations; estimation of a model of the noise affecting the observed system. Estimation of nonlinear black-box models is based on methods like nonlinear ARX and Hammerstein-Wiener models.

In the modern control systems models of artificial intelligence may be used for estimation of nonlinear complex systems, of high dimensions, with many variables. Such models may be developed using: fuzzy logic, neural networks, Bayesian networks, genetic algorithms, knowledge base systems, expert systems.

4.1 Estimation Based on Linear Models

A general case model is the *Box-Jenkins model*, summarized as:

$$y(t) = G(q,\theta)u(t) + H(q,\theta)e(t) \tag{25}$$

where G and H are rational transfer functions of the shift operator q for the time discrete model

$$G(q,\theta) = \frac{\sum_{i=1}^{n_b} b_i q^{-n_k-i+1}}{1+\sum_{i=1}^{n_f} f_i q^{-i}},\ H(q,\theta) = \frac{1+\sum_{i=1}^{n_c} c_i q^{-i}}{1+\sum_{i=1}^{n_d} d_i q^{-i}} \tag{26}$$

θ is the parameter vector thus contain the coefficients b_i, c_i, d_i, f_i of the transfer functions and e is the white noise

The model is described by the structural parameters n_b, n_c, n_d, n_f and n_k. When these have been chosen it remains to adjust the parameters b_i, c_i,

d_i, f_i to data.

Some special cases are: - the *output error model* (OE), where the properties of the disturbance signals are not modeled and H=1; the *ARMAX model* – the auto-regression and a moving average of white noise, when

$$F(q) = D(q) = A(q) = 1 + \sum_{i=1}^{n_a} a_i q^{-i} \quad (27)$$

and the *ARX model*, where in the above case of ARMAX other simplification is done C(q)=1.
Starting from (…) it is possible to predict what the output y(t) will be, based on measurements of u(t), y(t). The prediction of y(t) is obtained with the general expression:

$$\hat{y}(t) = [1 - H^{-1}(q,\theta)]y(t) + H^{-1}(q,\theta)G(q,\theta)u(t) \quad (28)$$

which have special cases for OE and ARX.

The principle of minimizing the prediction errors is used to fit the parameterized models to data.

The output y at time t is thus computed as a linear combination of past outputs and past inputs. It follows, for example, that the output at time t depends on the input signal at many previous time instants. This is the system dynamics. The identification problem is then to use measurements of u and y to figure out: the coefficients in this equation; how many delayed outputs n_f to use in the description. If the time delay in the system is n_f that, from the equation we may see that it takes nh sample periods before a change in u will affect y. How many delayed inputs n_b to use.

4.2 Estimation Based on Fuzzy Logic

In the case of estimation based on *fuzzy logic* the model is a fuzzy system. Such a fuzzy system has the structure from Fig. 9.

In this structure an input interface of fuzzification transforms the crisp inputs *u* in fuzzy information *A*, applied to an inference procedure. The inference is working using a rule base of the fuzzy model. The crisp output *y* of the fuzzy model is obtained from the fuzzy information *B* of the inference applying a defuzzification method.

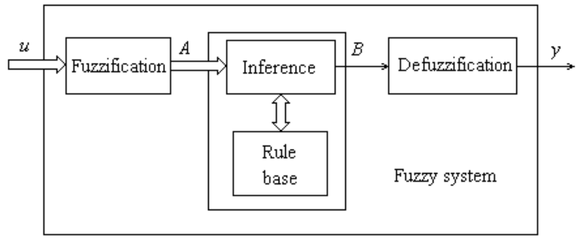

Fig. 9. Fuzzy model

The inference is a computational method used in computers to apply the fuzzy reasoning from the rule base. An example of inference is presented in Fig. 10.

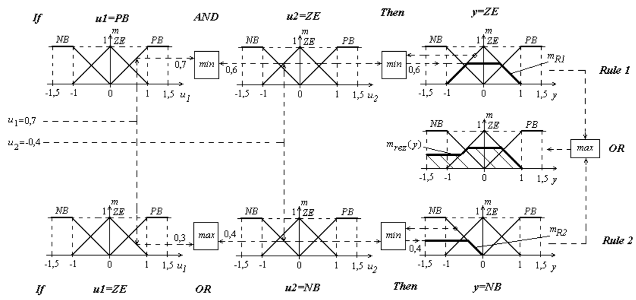

Fig. 10. Fuzzy inference

In this inference method the crisp inputs u_1 and u_2 are fuzzified through membership functions assigned to the fuzzy values (NB, ZE, PB) from the rule base. The rule base are computed using fuzzy operations as AND, OR, implemented with minimum or maximum. The output fuzzy set, described by a membership function, is computed with the fuzzy operation OR. These computations are made for all the rules of the rule base. And the result is the fuzzy information B. The output *y* is the most significant value from the universe of discourse (the definition set of the membership function) of the output membership function.

4.3 Estimation Based on Neural Networks

The same identification algorithms may be implemented using *neuronal networks*. In this, case a feedforward neural network, with continuous values, with two hidden layers of neurons, working as multifunction approximation is recommended. The structure of a multilayer neural network with m inputs u_i, i=1,...,m and n outputs y_i, i=1,...,n is presented in Fig. 11.

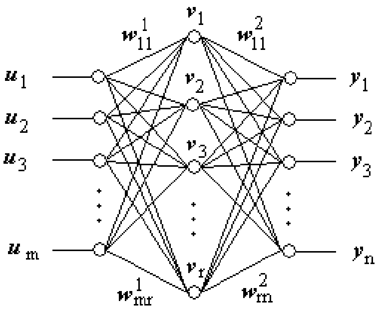

Fig. 11. Multilayer feedforward neural network

This neural network has weights for the internal connections w_{ij}^k, and each neuron has is own bias. The neuron acts like the following functions:

$$v_i = f_a\left(\sum_{j=1}^{m} w_{ji}^1 u_j + b_i\right) \quad (29)$$

where f_a is the activation function. Such activation function are the sigmoid th(x) for the neurons from the hidden layers from the interior of the neural network and the linear function y=x, for the neurons from the output layer. The neural network transfer function is:

$$y_i^q = f_{a2}(h_i^q) = f_{a2}\left(\sum_j w_{ji}^2 v_j^q + b_i^2\right) = = f_{a2}\left(\sum_j w_{ji}^2 f_{a1}\left(\sum_k w_{kj}^1 u_k^q + b_j^1\right) + b_i^2\right) \quad (30)$$

The neural identification has the block diagram from Fig. 12.

In this case the model is a neural network. The neural model is obtained by training (learning) the neural network with training sets (u_i, y_i), i=1, N, obtained from real measurements from the distributed parameter systems, achieved using sensor networks. A cost function (31) is imposed for training.

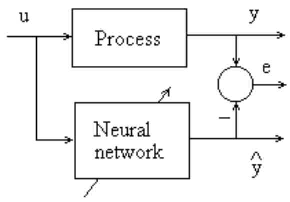

Fig. 12. Direct neural identification

$$E(w) = \frac{1}{2}\sum_{q,i}(y_i^q - y_i^{qd})^2,\ \ i = 1,..., p \quad (31)$$

A training method, based on error backpropagation is used. For example the Levenberg Marquard method, using a cvasi-Newton method to minimize the cost function assures the small number of iterations to obtain the appropriate weight and biases values. A rule of weight updating is applied:

$$\Delta w_{kj} = -\eta\frac{\partial E}{\partial w_{kj}} = \eta\sum_{qi}\delta_i^{2q} w_{ji}^2 S'(h_j^q)u_k^q = = \eta\sum_q \delta_j^{1q} u_k^q \quad (32)$$

Developing of neural mode has the principle described in Fig. 13.

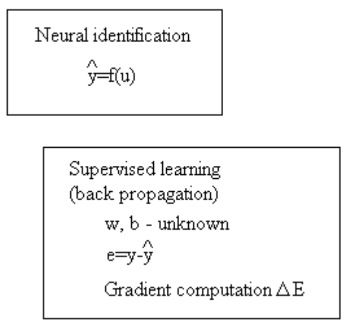

Fig. 13. Diagram of neural identification development

As we said above, a supervised learning (by backpropagation) is used to obtain the best values of the unknown weights w and biases b, propagating back through the network the training output error

$$e = y - \hat{y} \quad (33)$$

computing the gradient ΔE.

5 Malicious Node Detection

In this example a strategy based on antecedent values provided by each sensor for detecting their malicious activity is presented. At each time moment the sensor's output is compared with its estimated value computed by a robust *autoregressive neural predictor*. In case that the difference between the two values is higher then a chosen threshold, the sensor node becomes suspicious and a decision block is activated. We present the neural estimation structure based on autoregression, the model of the heat conduction in the plane, sensor deployment, the neural network structure, the neural training characteristics, the sensor value and the estimate, the sensor error and an example of sensor network measurements.

5.1 Detection Strategy

The strategy of detection considers an *autoregressive (AR) model* that approximates the time evolution of the measured values provided by each sensor:

$$x(t) = a_1 \cdot x(t-1) + ... + a_n \cdot x(t-n) + e(t) \quad (34)$$

where x(t) is the series under investigation (in our case is the series of values measured by the same sensor), a_i are the auto regression coefficients, n is the order of the auto regression and e is the noise.

The model (34) may be implemented using a *feedforward neural network* with continuous values. The inputs of the neural network are the measured values of the sensor, at previous *n* time moments. The coefficients a_i will be given by the weights and biases of the neurons from the hidden layers of the neural network. The output of the neural network will be the estimate at the time t of the sensor value:

$$x(t) = a_1(w_i, b_j) \cdot x(t-1) + ... + a_n(w_i, b_j) \cdot x(t-n) + \xi(t) \quad (35)$$

The weights and biases values are computed by training, knowing on-line or off-line a set of training under the form of a time series x(t), x(t-1),…,x(t-n).

The strategy uses the time series of measured data provided by each sensor and relies on an autoregressive neural predictor placed in base stations (Fig. 14).

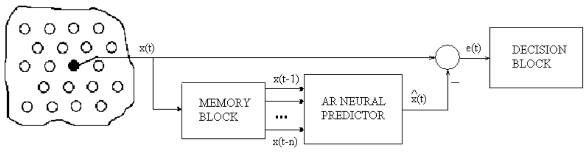

Fig. 14. Malicious node detection block diagram

The detection principle is the following: identifying a malicious node that will try to enter false information into the sensor network comparing its output value $x(t)$ with the value $\hat{x}(t)$ predicted.

The proposed methodology is described as follows: At every instant t the estimated value $\hat{x}_A(t)$ is computed relying only on past values $x_A(t-1)$, …, $x_A(0)$ and parameter estimation and prediction is used, as in the following steps. First the parameters w_i, b_i of the neural network are determinate, using the Levenberg Marquardt method. *A training set* including all the possibilities of the sensor network behavior is used. The neural network is trained to obtain a small training error and a high degree of generalization. The neural network is test with *a test set*. Second, *the prediction value* $\hat{x}(t)$ is obtained using the following equation:

$$\hat{x}_A(t) = a_1(w_i, b_j) \cdot x_A(t-1) + ... + a_n(w_i, b_j) \cdot x_A(t-n) + \xi(t) \quad (36)$$

After that, the present value $x_A(t)$ measured by the sensor node is compared with its *estimated value* $\hat{x}_A(t)$ by computing *the error*:

$$e_A(t) = x_A(t) - \hat{x}_A(t) \quad (37)$$

If this error is higher than *a threshold* ε_A then the sensor A will be considered to be a potentially corrupted sensor and the decision block will be activated. Here, based on a database containing the known attacks models, a knowledge-based system can take the decision to expel the malicious node from the network topology (Fig. 14).

There is no simple method to establish the correct *model order* in case of an AR model. In this case there are two parameters that influence the decision: the type of data measured by sensors and the computing limitations of the base stations. Because both of them are a priori known an off-line methodology is recommended. Realistic values are between 3 and 6.

The structure of the neural network is established after iterative trainings.

5.2 Process Model

The propagation of a temperature wave, in a homogenous planar field, is considered, where several sensor nodes $S_{i,j}$ with I=1,…,N and j=1,…,M, being a part of a sensor network, have been deployed. These sensors are measuring the local temperature θ [^{o}C]. A possible malicious node, to be detected, is denoted by S_A. An auto-regression neural network model is developed to estimate the temperature value provided by the sensor A: $\hat{x}_A(t) = \hat{\theta}_A(t)$, by taking into consideration the previous values of the data provided by sensor x_A(t-1), x_A(t-2), …, x_A(t-n).

The time distribution of the temperature θ through the homogenous medium in space is $\theta(z,t)$, at the moment t, at distance z from the heat source.

The heat conduction, when neglecting the heat loses in the environment, is described by the heat equation [19],[20]:

$$c_\theta \frac{\partial^2}{\partial z^2}\theta(z,t) = \frac{\partial}{\partial t}\theta(z,t) \quad (38)$$

where c_θ is the heat conductivity coefficient of the medium.

In order to investigate how the strategy works the function $\theta = \theta(z,t)$ is discretised into the aggregates $\theta_{j,k}$ (temperature value provided by $S_{j,k}$) measured at the distance $z_{j,k}$ from the origin. The goal is to obtain the temperature θ_A measured by the corresponding sensor (S_A).

The energy conservation is governed for each point in the field by the following equation:

$$\frac{d}{dt}W_{j,k} = P_{in}^{j,k} - P_{out}^{j,k} \quad (39)$$

where $W_{j,k}$ is the energy stored in point (j,k), $P_{in}^{j,k}$ is the input power in the point and $P_{out}^{j,k}$ is the output power from the point. The space model of the sensor deployed in the field with the heat sources is presented in Fig. 5.

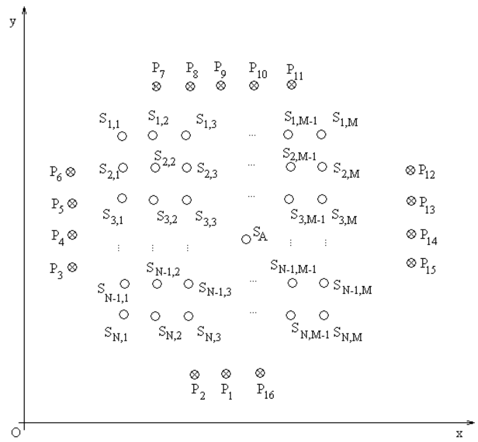

Fig. 15. Sensor deployment

The sensor S_A measures the temperature θ_A in a point in this space. Let the heat capacity of each point be denoted C and the heat transfer coefficient between the points $K_i^{j,k}$. These give the equation in time of the heat diffusion:

$$\frac{d}{dt}C\theta^{j,k}(t) = \sum_{i1} K_{i1}^{j,k}[\theta_{i1}^{j,k}(t) - \theta^{j,k}(t)] - \\ - \sum_{i2} K_{i2}^{j,k}[\theta_{i2}^{j,k}(t) - \theta^{j,k}(t)] \quad (40)$$

A discrete time equivalent equation of (40), with a chosen adequate sample period *h* is used. Each cell of sensors is receiving inputs from the around medium, from *r* sources with powers P_i, *i*=1, …, *r*, positioned around the network. The heat sources P_i are positioned in different points in the coordinate system *x*O*y*. Some coordinate transformations may be done and the sources may be moved in the adjacent points of the network.

5.3 Sensor Network Measurements

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 transient temperature characteristics measured for temperature monitorization in a chamber are presented in Fig. 16.

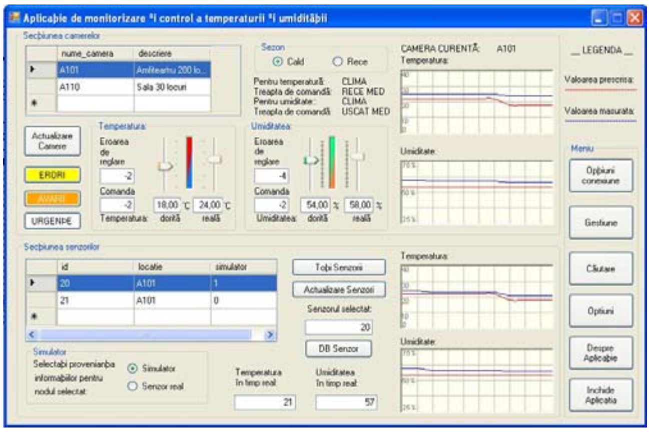

Fig. 16. Temperature transient characteristics measured with the sensor network

The user interface allows some facilities, as: administration, searching, connections options and so on.

5.4 Neural Network

The neural network used for estimation is a feedforward neural network, with continuous values. It has 4 inputs, the sensor values at 4 antecedent time moments: $x_A(t-1)$, $x_A(t-2)$, $x_A(t-3)$ and $x_A(t-4)$. The output layer has one neuron for the estimated temperature. The structure of it is presented in Fig. 17.

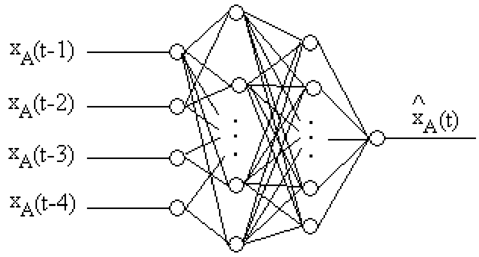

Fig. 17. The structure of the neural network

According to Kolmogorov's theorem two hidden layers are used, with biases, to obtain a reduced error of approximation of the estimate. The first and the second hidden layers have a reduced number of neurons, 32 and 16 neurons, respectively. These numbers resulted after some iterative training. The activation functions of the neural network are the hyperbolic tangent function for the hidden layers and the first-order linear function for the output layer.

The training of the neural network with a training set, which cover the entire possible scenario in the field. The input data for estimation is a time series of the temperature sensor S_A, as the state of the heat diffusion model (40). This time series is obtained using sums of the traveling temperature waves, generated by the heat sources P_i. The temperatures propagate through to the sensor S_A. The training set was obtained using present and anterior values of the sensors, ($\theta_A(t-1)$, $\theta_A(t-2)$, $\theta_A(t-3)$, $\theta_A(t-4)$; $\theta_A(t)$) taken from the transient responses of the model (38÷40). The method chosen for training was the Levenberg-Marquardt method. The sum square error after 9 training epochs is presented in Fig. 18.

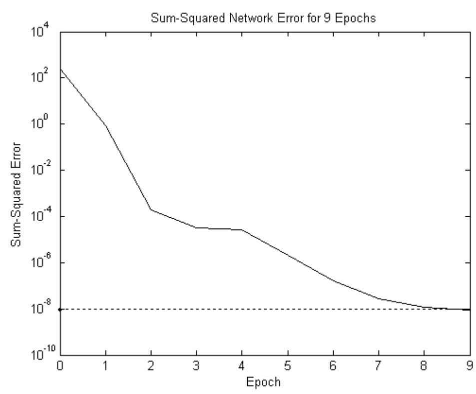

Fig. 18. The training error

At a specific time moment (*t*=400) the sensor was corrupted. Some different sets of candidate models for the model structure could be experimented. A 4th order estimation general model was chosen. With weights and biases it has the expression:

$$\hat{x}_A(t) = \sum_{i=1}^{4} a_i(w,b) \cdot x_A(t-i) + \xi \tag{41}$$

This autoregressive neural estimation is applied for the sensor S_A.

5.5 Experimental results

The estimated temperature $\hat{x}_A(t) = \hat{\theta}_A(t)$ for the sensor S_A is presented in Fig. 19, over the original time series $x_A(t)$.

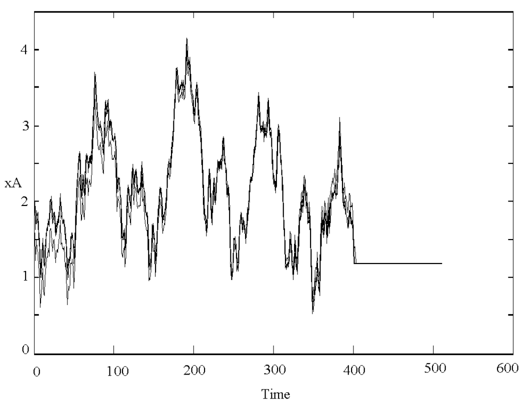

Fig. 19. Sensor value and the estimate

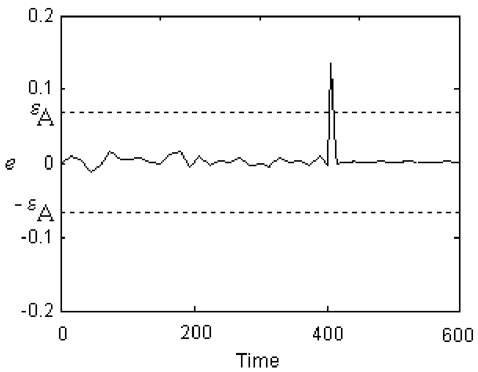

Fig. 20. Sensor error

The error $e_A(t) = x_A(t) - \hat{x}_A(t)$ is presented in Fig. 20.

We may see the error appearance at the time moment 400 s, caused by a fault at the node x_A.

The estimated signal follows the real signal after a small delay.

6 Conclusions

A short survey of three topics: modern sensor networks, distributed parameter systems and estimation techniques, specially using artificial intelligence tools, to be involved in the new domain of identification of distributed parameter systems, based on sensor networks and artificial intelligence.

Modern sensors are smart, small, lightweight, portable devices, with a communication infrastructure, used to monitor and record specific parameters. They have low cost and are low energy devices, realized in nanotechnology. Some of their technical characteristics are presented. As smart and small devices they are capable to be implemented in large distributed parameter systems.

Sensor networks have in their structure hundred and thousands of ad-hoc tiny sensor nodes spread across a geographical area. Sensor nodes collaborate among themselves to establish a sensing network. The sensor network provides access to information anytime, anywhere, by collecting, processing, analyzing and disseminating data. The network actively participates in creating a smart environment. A sensor network is acting as a distributed sensor in a distributed parameter system. Sensor network topics, sensor network architectures and sensor network applications are presented. Applications of data acquisition of physical and chemical properties, at various spatial and temporal scales, as in distributed parameter systems, for automatic identification, measurements over long period of time.

Some examples of distributed parameter systems with large application in practice are presented: the process of heat conduction, applications related to electricity domain, motion of fluids, processes of cooling and drying, phenomenon of diffusion and other applications. All these processes have the same equations with partial derivatives.

Using system identification techniques we may build accurate and simplified models of distributed parameter systems, from noisy time-series data obtained with sensor networks. The identification techniques are useful for applications ranging from control systems, fault detection and diagnosis, signal processing to time-series analysis. Methods to estimate linear back box models and models of artificial intelligence, as fuzzy logic and neural network are presented.

A case study of malicious nod detection is presented. The strategy of detection is based on a neural autoregression method in the process of plane heat propagation. The paper presents: the model of the heat conduction in the plane, sensor deployment, an example of sensor network measurements, the neural network structure, the neural training characteristics, the sensor value and the estimate and the sensor error.

References:

[1] C. Volosencu, Identification in Sensor Networks, in *Automation & Information: Theory and Advanced Technology, Proceedings of the 9th WSEAS Int. Conf. on Automation and Information (ICAI'08)*, WSEAS Press, 2008, pp. 175÷183.

[2] H. Zhang, J.M.F. Moura, B. Krogh, Estimation in sensor networks: a graph approach, *4th Int. Symp. on Information processing in sensor networks***,** Los Angeles, CA, 2005.

[3] H. Zhang et all., Estimation in sensor actuators arrays using reduced order physical models, *4th Int. Symp. Information Processing in Sensor Networks*, Los Angeles, CA, 2005.

[4] R. Novak, U. Mira, Boundary Estimation in Sensor Networks: Theory and Methods, *Information Processing in Sensor Networks: 2nd Int. Workshop*, IPSN 2003, Palo Alto, CA, 2003.

[5] D.I. Curiac, C. Voloşencu, A. Doboli, O. Dranga, T. Bednarz, Discovery of Malicious Nodes in Wireless Sensor Networks Using Neural Predictors, *WSEAS Transactions on Computer Research*, Issue 1, Vol. 2, Jan. 2007, pp. 38 – 44.

[6] C. Volosencu et. all., Malicion Node Detection in Sensor network Using Autoregression Based on Neural Network, *4th IFAC Conf. on Management and Control of Production and Logistics, MCPL2007,* Sibiu, 2007, pp. 571 – 577.

[7] H.T. Banks, K. Kunish, Estimation techniques for distributed parameter systems, *Systems & control: foundation & applications,* vol. 1, Note(s): XIII-315, 1989.

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

[9] M.P. Polis, R.E. Goodson, Parameter identification in distributed systems: A synthesizing overview, *Proceedings of the IEEE*, Jan. Vol. 64, Issue: 1, 1976, pp. 45- 61.

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

[11] J.E. Lagnese, D.L. Russell, Control and Optimal Design of Distributed Parameter Systems, *Mathematics and Its Applications*, Vol. 70, Springer-Verlag New York, NY, 1995.

[12] M.A. Demetriou, Adaptive identification of second-order distributed parameter systems, *Inverse Problems,* no. 10**,** 1994, pag. 261-294.

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

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

[15] G.J. Pottie, W.J. Kaiser, Wireless Integrated Network Sensors. *Communications of the ACM,* vol. 43, 2000.

[16] J. Feng, F. Koushanfar, M. Potkonjak, System-Architectures for Sensor Networks Issues, Alternatives and Directions, *Proc. of the 2002 IEEE Int. Conf. on Computer Design (ICCD'02)*, Freiburg, 2002, pp.226-231.

[17] L. Tong, Q. Zhao, S. Adireddy, Sensor Networks with Mobile Agents, *Proceedings IEEE 2003 MILCOM*, Boston, USA, 2003, pp.688-694.

[18] C. Volosencu, *Sisteme fuzzy si neuronale*, Ed. Politehnica, Timisoara, 2007.

[19] G.B. Folland, *Introduction to partial differential equations*, Princeton University Press, 1995.

[20] M.N. Rosculet, M. Craiu, *Ecuatii diferentiale aplicative*, Ed. Academiei RSR, Bucuresti, 1979.

[21] D. Basmadjian, *The Art of Modeling in Science and Engineering*, Chapman & Hall, CRC, Boca Raton, 1999.

[22] K. Zheng, A. Hoo, M. J. Piovoso, Finite Dimensional Modeling and Control of Distributed Parameter Systems, *Proc. American Automatic Control Conf.*, Anchorage, 2002.

[23] R. González-García**,** R. Rico-Martínez**,** I. G. Kevrekidis, Identification of distributed parameter systems: A neural net based approach, *European Symp. on Computer Aided Process Engineering*, Vol. 22, Sup. 1, 1998, p. S965-968.

[24] D. Coca, S.A. Billings, Direct parameter identification of distributed parameter systems, *Int. J. of Systems Science*, Vol. 31, No. 1, Jan., 2000, pp. 11-17(7).

[25] G. B. Giannakis, Distributed Estimation Using Wireless Sensor Networks, *The 12th WSEAS Int. Conf. On Systems*, Heraklion, Crete Island, Greece, 2008.

[26] C. Volosencu, D.I. Curiac, A. Doboli, O. Dranga, Knowledge Based System for Reliable Perimeter Protection Using Sensor Networks, *Int. Conf. Winsys2007*, Barcelona, 2007.

[27] B. Krishnamachari, A Wireless Sensor Networks Bibliography, *Technical Report*, University of Southern California, 2007.

[28] L. Ljung, *System Identification, theory for the user*, Prentice Hall, Upper Saddle River, NJ, 1999.

[29] L. Ljung, T. Glad, *Modeling of Dynamic Systems*, Prentice Hall, Englewood Cliffs, N.J. 1994.

[30] T. Söderström, P. Stoica, *System Identification,* Prentice Hall International, London. 1989.

[31] Sjoberg, J., et. all., Non linear black box modeling in system identification: an unified overview, *Automatica*, 33, 1997, 1691-1724.

[32] L.H. Chiang, E.L. Russell, R.D. Braatz, *Fault Detection and Diagnosis in Industrial Systems*, Springer Verlag, London, 2001.