Environmental Monitoring Based on Sensor Networks and Artificial Intelligence

Constantin Volosencu

Abstract — This paper presents some considerations related to the applications in environment monitoring of some concepts as: estimation, fault detection and diagnosis, theory of distributed parameter systems, artificial intelligence, with its tool adaptive-network-based fuzzy inference and the intelligent wireless ad-hoc sensor networks. All these concepts allow treatment of large, complex, non-linear and multivariable system of the environment by learning and extrapolation.

Keywords — Sensor networks, artificial intelligence, adaptive network based fuzzy inference, estimation techniques.

I. INTRODUCTION

The environment may be seen as a complex ensemble of different distributed parameter systems, described with partial differential equations [1]. Sensor networks [2] have large and successful applications in monitoring the environment, they been capable to measure, as a distributed sensor, the physical variables, on a large area, which are characterizing the environment and to communicate at long distance the measured values, form the distributed parameter environmental processes [3, 4, 5]. Using the modern intelligent wireless sensor networks multivariable estimation techniques may be applied in environment monitoring, seen as distributed parameter systems. Based on these concepts environment monitoring becomes more easily and more performing (Fig. 1).

Fig. 1. Scientific domains for environmental monitoring

Environmental monitoring based on sensor networks was studied in recent papers. Some related work is surveyed as follows. The paper [6] presents some research consideration related the changes of urban spatial thermal environment, for sustainable urban development, to improve the quality of human habitation environment. The urban thermal phenomenon is revealed using thermal remote sensing imagery, based on the instantaneous radiant temperature of the land surfaces. An architecture fo sensor network for environment is presented in [7]. Environmental pollution and meteorological processes may be studied using various kinds of environmental sensor networks. The modern intelligent sensor networks comprise automatic sensor nodes and communication systems which communicate their data to a sensor network server, where these data are integrated with other environmental information. The paper [8] presents the design and implementation of a wireless sensor network for monitoring environmental variables and evaluates its effectiveness. It has application in environment variable monitoring such as: temperature, humidity, barometric pressure, soil moisture and ambient light, for research in agriculture, habitat monitoring, weather monitoring and so on. To improve the capacity of the environmental sensor networks different techniques may be used. The paper [9] is using a model predictive control for optimal resource management in environment sensor networks, for with application at spatio-temporal events of a coastal monitoring and forecast system. The paper [10] presents and application at the estimation of atmospheric pressure using a wireless sensor network, which is randomly distributes. The estimation error is discussed and a design criterion is proposed. The authors have contribution in the field of monitoring distributed parameter systems based on sensor networks and estimation using adaptive-network-based fuzzy inference [11].

The paper presents a short survey of the main characteristics of the above topics involved in the problem of the environmental monitoring, some principles and technical data of modern sensor networks, some examples of distributed parameter systems, with their mathematical models, useful in environment description. The second paragraph presents some equation useful in modeling environmental processes. The third paragraph presents some examples of modeling and simulation of environmental temperature variation. The fourth paragraph presents some technical data of the sensor network used in practical experiments. The fifth paragraph presents a case study of environmental temperature estimation base on auto-regression and ANFIS. The main results and future perspectives are presented in conclusion.

Manuscript received August, 11, 2010.
C. Volosencu is with the “Politehnica” University of Timisoara, Faculty of Automatics and Computers, Department of Automatics and Applied Informatics, Timisoara, 300223, Romania, phone 0040-(0)724369136, e-mail: constantin.volosencu@aut.upt.ro.

II. EQUATIONS FOR ENVIRONMENTAL SYSTEM

The environment system, a complex system of distributed parameter systems, may be described using partial differential equations. These equations are used to formulate problems involving functions of several variables, such as the propagation of sound or heat, electrostatics, electrodynamics, fluid flow. Distinct physical phenomena from the environment have identical mathematical formulations, and the same underlying dynamic governs them. Some examples of distributed parameter systems are presented as follow [1]. Diverse categories of systems have specific characteristics that are important in their investigation, simulation, prediction, monitoring and diagnosis. The most important domains of applications are: the processes of heat conduction, with propagation of heat in anisotropic medium; propagation of heat in a porous medium, processes of transference of heat between a solid wall and a flow of hot gas; applications related to electricity domain as electrostatic charges in atmosphere; the motion of fluid, the processes of cooling and drying, phenomenon of diffusion. Other applications are: the growing of the gas particles in a fluid, the temperature modification in the air mass.

For two of the above processes some equations are given as follows. The function of the object’s temperature is \( \theta \,\) a point in the space. If different points of object have different temperatures, \( \theta(P,t)\neq ct. \) then a heat transfer will take place, from the warmer parts to the less warm parts. The vector \( \text{grad} \theta \) has its direction along the normal at the level surface for \( \theta=ct. \) in the sense of \( \theta \) rising. The law of heat propagation through an object in which there are no heat sources:

\[
\frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x} \left( k \frac{\partial \theta}{\partial x} \right) + \frac{\partial}{\partial y} \left( k \frac{\partial \theta}{\partial y} \right) + \frac{\partial}{\partial z} \left( k \frac{\partial \theta}{\partial z} \right)
\]

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

\[
F(t,P) = F(t,x,y,z)
\]

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

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

The initial conditions or of the limit conditions have physical significance. They are given by the equation:

\[
\left. \theta(x,y,z,t) \right|_{t=0} = f(x,y,z)
\]

For the plane motion of viscous fluids let consider an incompressible, viscous fluid of constant density \( \rho \), 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

\[
\frac{\partial v_x}{\partial t} + v_x \frac{\partial v_x}{\partial x} + v_y \frac{\partial v_x}{\partial y} = -\frac{1}{\rho} \frac{\partial p}{\partial x} + \nu \Delta v_x
\]

\[
\frac{\partial v_y}{\partial t} + v_x \frac{\partial v_y}{\partial x} + v_y \frac{\partial v_y}{\partial y} = -\frac{1}{\rho} \frac{\partial p}{\partial y} + \nu \Delta v_y
\]

where \( p \) is the pressure in this point, \( \nu = \frac{\mu}{\rho} \), \( \mu \) is the viscosity coefficient.

At the equations (5) the equations of continuity are added

\[
\frac{\partial v_x}{\partial x} + \frac{\partial v_y}{\partial y} = 0
\]

The current function is introduced

\[
v_x = -\frac{\partial \phi}{\partial y}, \quad v_y = \frac{\partial \phi}{\partial x}
\]

The distributed parameter systems have general mathematical models in continuous time and space as partial differential equation, of parabolic form, as:

\[
\frac{\partial \theta}{\partial t} = c_1 \nabla^2 \theta + c_2 \theta + Q
\]

where the variables \( \theta(\zeta,t) \) are depending on time \( t \in \mathbb{R} \) and on space \( \zeta \in \mathbb{R} \), where \( \zeta \) is \( x \) for one axis, \( (x,y) \) for two axis or \( (x,y,z) \) for three axis, \( c_1, c_2 \) and \( c_3 \) are coefficients, which could be also time variant and \( Q(\zeta,t) \) is an exterior excitation, variable on time and space.

So, in the general case, an implicit equation may be written:

\[
f \left( \frac{\partial \theta}{\partial t} + \frac{\partial \theta}{\partial \zeta} + c_1 \frac{\partial \theta}{\partial \zeta} + c_2 \zeta \frac{\partial \theta}{\partial \zeta} + \ldots \right) = 0
\]

For the partial differential equations some boundary conditions may be imposed to establish a solution. So, when the variable value of the boundary is specified there are Dirichlet conditions:

\[
c_2 \theta = q
\]

And, when the variable flux and transfer coefficient are specified there are Neumann conditions:

\[
c_1 \nabla \theta + c_3 \theta = 0
\]

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

\[
\theta(0,t) = \theta_0, \quad t \in [0,T], \theta(0,0) = 0, \quad \zeta \in [0,l],
\]

\[
\theta(l,t) = \theta_l, \quad t \in [0,T]
\]

A system with finite differences may be associated to the equations. For this purpose the space \( S \) is divided into small pieces of dimension \( l_p \). In each small piece \( S_{pi}, i=1,\ldots,n \) of the space \( S \) the variable \( \theta \) could be measured at each moment \( t_k \), using a sensor from the sensor network, in a characteristic point \( P(\zeta_i) \), of coordinate \( \zeta_i \). Let it be \( \theta^k \) the variable value in the point \( P(\zeta_i) \) 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.

Combining the equations a system of equations with differences results for the parabolic equation:

\[
f_p(\theta_{t}, \theta_{x1}, \theta_{t+1}, \theta_{x11}) = 0
\]

Taking account of equations (13) it is obvious that several estimation algorithms may be developed as follows, based on the discrete models of the partial derivative equations.
III. MODELING AND SIMULATION

Environment behavior may be modeled with the equation from the above paragraph. Using these models some analysis in time and space domains may be done. Some transient characteristics of the temperature are presented for 101 samples. The nodes and meshes structure for a sensor network with reduced number of sensor, in this case 13, is presented in Fig. 2.

![Fig. 2. Nodes and meshes for heat transfer in plane](image)

The temperature variation in 3D is presented in Fig. 3, at a certain time moment.

![Fig. 3. Temperature variation in space](image)

Temperature isotherms in plane are presented in Fig. 4.

![Fig. 4. Temperature isotherms](image)

Temperature variation in space in 4 nodes is presented in Fig. 5.

![Fig. 5. Temperature variation in time](image)

Identical characteristics may be obtain for other distributed parameter systems involved in environmental modeling.

IV. SENSOR NETWORK

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. 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. 6.

![Fig. 6. The structure of a modern sensor](image)

The constructive and functional representation of a sensor network is presented in Fig. 7.

![Fig. 7. Sensor network](image)

The sensor $S_A$ measures the temperature $\theta_A$ in a point in this space.

A Crossbow sensor network was used in practice (Fig. 8). The basic components of the sensor network are: a base station and sensor nodes. The base station is wireless, with computing energy and communication resources, which is acting like an access gate between the sensor nodes and the end user. The base station used in practice is an IRIS / MICA module, a gete MIB250, which is functioning connected at USB. The senor nodes have two components. The processor/radio module IRIS/MICA are activating the measuring system of small power.
They are working at the frequency of 868/916 MHz or 2.4 GHz. The sensor circuit MTS400 which is including temperature sensor. The sensor network has also a software for data acquisition MoteView, which is reading data from a data base PostgreSQL. The interface is presented in Fig. 9.

The sensor network is working in real time with a driver which assures data acquisition from the base station.

V. MONITORING APPLICATION

The application is using the following algorithms, obtained from the above general discrete function:

\[ \theta_i^{k+1} = f(\theta_i^k, \theta_i^{k+1}, \theta_i^{k+2}, \theta_i^{k+3}) \]  

(14)

It estimates the value of the variable \( \theta_i^{k+1} \) 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 \( t_{k+3} \).

The function \( f \) may be a linear one, as a linear combination of measured variables or a nonlinear one. The linear estimation algorithm may be obtained with the least square method.

A study case where the function is made by adaptive-network-based fuzzy inference is presented in the paper.

The number of inputs is 4 and it is a condition of determination. The ANFIS procedure is well known and it may use a hybrid learning algorithm to identify the membership function parameters of the adaptive system. A combination of least-squares and backpropagation gradient descent methods is used for training membership function parameters, modeling a given set of input/output data.

The structure of the estimation and detection system is presented in Fig. 10.

The measured values from sensors are memorized and a multivariable estimation algorithm is applied. Based on the error between the measured and estimated values a decision is taken. The error has the equation:

\[ e_A(t) = \| x_A(t) - \hat{x}_A(t) \| \]  

(15)

The following method of monitoring is recommended. The sensors must be placed in the field according to the meshes structured under the form of nodes and triangles. The neural network is trained in transient regimes. With the ANFIS algorithm future states of the process may be estimated. In practice the following steps occur: -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;

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

A short description about the ANFIS and its function approximating property is provided as it follows. The number of inputs depends on the algorithm type. For the 1st and 2nd algorithms there are 4 inputs, because of the first order derivation in time of the parabolic model. For the 3rd and the 4th algorithms there are 6 inputs, because of the second order derivation in time of the hyperbolic model.

The comparison transient characteristics for training and testing output data are presented in Fig. 12. The average testing error is \( 2.017 \times 10^{-5} \). Number of training epochs is 3. The sensor network is controlled by a virtual instrument, made using LabView. The virtual instrument for temperature measurement and estimation is presented in Fig. 13. The virtual instrument for temperature estimation error is presented in Fig. 14. The sample period was 9 s.
Good values are obtained for estimation errors.

VI. CONCLUSION

This paper presents some considerations on environmental monitoring using sensor networks and estimation techniques based on ANFIS, one of the main tools of artificial intelligence. The positioning of sensors in the field may be done according to optimal nodes and triangular meshes of a modeling and simulation of the environmental process based on distributed parameter system theory. After acquiring the measured values from the area covered by sensor networks, some estimation techniques may be applied. The auto-regression estimation linear or ANFIS models may be used. This methodology can be efficiently implemented on sensor network base stations, so there is no need for other hardware resources. An example of generated meshes and temperature estimates is presented. The sensor network is seen as a “distributed sensor”. Algorithms based on regression using adjacent nodes also may be used.

ACKNOWLEDGMENT

This work was made in the frame of the CNCSIS – UEFISCSU, PNII – IDEI_PCE_ID923 grant.

REFERENCES