Real-Time Modeling in Pervasive Mining

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***Abstract*—This paper introduces an integrated design for real-time plant modeling at a copper mine, using Support Vector Machines (SVM), Neural Networks, and new technologies such as Machine-to-Machine (M2M) and Cloud Computing with an Android client. This solution was designed for a plant inside a copper mine which cannot tolerate interruption and for which their in situ modeling, in real time, is an essential part of the system to control aspects such as instability by adjusting their corresponding parameters without stopping the process.** *(Abstract)*

Keywords: mining; modeling; support vector machines; pervasive; machine-to-machine; cloud; neural networks (key words)

I. INTRODUCTION

Several dramatic accidents that have occurred in the mining sector have turned the spotlight on safety and the need for stricter supervision in mining operations. In this respect there is an urgent need to deploy new technologies in order to enhance the safety of miners and processes inside the mine. Several efforts have been made in this direction and the trend is to automate miner´s tasks as much as possible. This may be done by using new generation telecommunications [1] and computer technologies for accessing resources inside the mine. Enhancements of automation and remote operations, helped by mobile devices applications [2] will allow employees to supervise remotely the production tools and to have access to applications on servers outside the mine without leaving it.

In this work, we apply the concepts introduced above to solve the plant monitoring problem (dynamic system) for control and optimization purposes, using modeling tools. In particular, we use a virtual sensor model to estimate in real-time the value of a physical parameter which cannot be measured directly without stopping the process. The knowledge of this value on-site, in real-time, is indispensable to control aspects such as instability and optimization of the whole process. It will also contribute to enhance mine safety.

The proposed system includes the machine-to-machine (M2M) telecommunications platform, a server in the cloud that runs a modeling method (based on neural network, support vector machines, or other) and a mobile client inside the mine.

This is an ongoing project, and at this stage, it is still under development. Machine-to-machine communications must be supported by operators, but this issue has not been solved yet. We are currently working on the development of software interfaces for the mobile client, and on the server applications located in a private cloud.

The rest of the paper is organized as follows: Section II describes briefly the proposed general communications architecture. Section III introduces some terms and concepts related to the modeling of dynamic systems used in this work; Section IV presents a practical modeling application related to on-line/real-time estimation of states in a complex Semi-Autogenous Grinding process (SAG) in copper mining; and Section V concludes the paper.

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II. SYSTEM DESCRIPTION

We present a design that integrates modeling tools and new communications technologies at a copper mine, in order to monitor, control and optimize a particular process. In order to deploy the solution, we have considered semi-autonomous grinding. The model will be useful to estimate, using a virtual sensor and in real time, the filling level parameter of the grinding, since it is very important to control and optimize the process.

Using new communications technologies, the plant operator as well as the supervisors may know the filling label value at the same time and anywhere inside or outside the mine. This brings up pervasive mining, a system with wider coverage, higher communication efficiency, better fault-tolerance, and anytime anywhere availability.

The proposed design considers M2M communications, a client-server application with the server in the cloud, and an Android client inside the mine (Fig. 1).

In order to employ real-time modeling, a prior suitable, liable plant model must be selected. The process for determining this model is performed as follows:

- A set of initial real data (e.g., 2500 samples) are sent directly from the plant towards the server in the cloud. Here, the data are divided into three data sets, to train (e.g., 500 samples), validate (e.g., 1000 samples), and test (e.g., 1000 samples) the candidate models, which the operator has defined previously.
- Tools that may be used for constructing the plant's models include Neural Networks, Support Vector Machines (SVM) or any other suitable tools.
- The server sends the calculated models to the operator, who can choose the best by comparing the forecasting errors. At the same time, the graphics and related results are sent to the monitoring screen, located anywhere inside or outside the mine, and where the whole process is controlled.
- Once the operator has chosen the best modeling tool (in our case a variation of support vector machines), it will be used for real-time modeling, in order to monitor, control and optimize the process.

A. M2M Communications and Architectures

Fig. 2 illustrates the high-level M2M communications architecture. In this scenario multiple connectivity options are available to serve machine-to-machine (M2M) applications requiring connectivity between end devices. The M2M client device can connect with the server (M2M server) directly through a WAN connection, M2M gateway, or an aggregation point [3]. In our design, our server modeling application will be installed in this server inside the cloud.

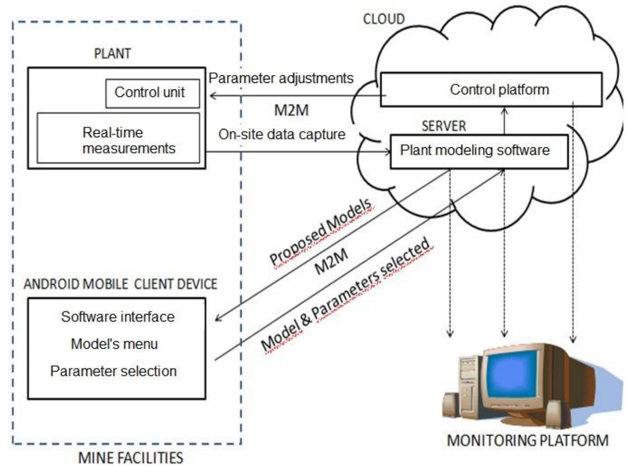

Figure 1. Modeling architecture

III. MODELING IN DYNAMIC SYSTEMS

A. Modeling tools

In order to get models for dynamic systems in production environments, several adaptive methods using approximation techniques have been developed. For instance, in [4], the authors used the Feed-Forward type Neural Networks (FFNN) to solve the problem of on-line identification of complex processes. As an important result, they encountered that FFNN converge satisfactorily in a few iteration cycles, showing better prediction capacity than recursive algorithms.

In [5] an observer model based on wavelet transform together with neural networks was successfully applied to solve the state observation problem of a dynamic system, when the dynamic model contains uncertainties or it is completely unknown.

In [6] the problem of on-line model identification for multivariable processes with nonlinear and time-varying dynamic characteristics has been solved using two online multivariable identification approaches with self-organizing neural network model structures. Two adaptive Radial Basis Function (RBF) neural networks have been defined, and the dynamic model is generated autonomously using the sequential input-output data pairs in real-time applications.

B. Model Performance

Once we had a set of the plant's real data, we divided it into three groups: to train, validate and test the model. However, when these goals are hampered by a lack of reliable experimental data it is necessary to construct a set of good quality, hypothetical data. In this sense an important tool to construct these data is the Lorentz model, which we used at the beginning of our work.

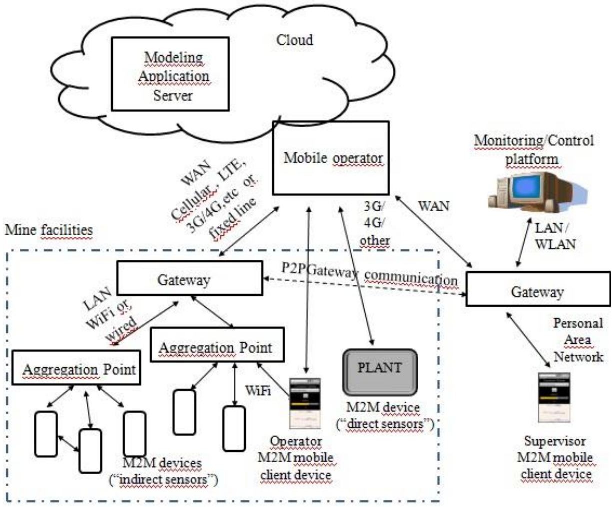

Figure 2. High-level M2M system architecture

This study will show a brief description of the Lorentz model that reveals the behavior of a dynamic system, and the related Forrester model which graphically represents a hypothetical plant that is being studied.

Data constructed from the Lorentz model are very valuable since they may represent the behavior of a plant inside a mine having chaotic outputs, and it is useful as a reference and for comparing purposes. If we have a deterministic, chaotic behavior, then reliable forecasting is possible and controlling the process in the mine becomes easier.

C. *Influence Diagram*

To study the behavior of dynamic systems, causal diagrams can be used to outline all the elements of a problem without going into the mathematical details in the possible model. An influence or causal diagram (also known as Forrester's diagram) represents influence relations that exist between the elements of a system, and therefore provides information about the structure.

As an example, Fig. 3 depicts the Forrester model corresponding to a plant whose behavior can be represented by the set of differential equations (1) related to the Lorentz model of a plant.

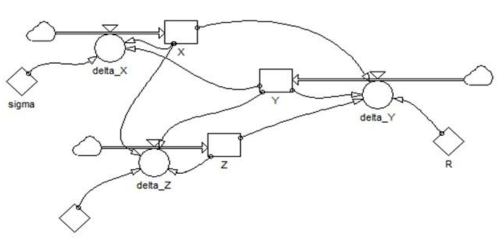

Figure 3. Forrester diagram for Lorentz model

A Forrester diagram shows the identified level, flow and auxiliary variables of a system. The level variables describe the states of the systems; flow variables refer to the input and output flows which influence the level; and auxiliary variables can determine a level or rate variable or another auxiliary variable, but it is not itself a level or rate variable of direct interest to be solved within the model. A Forrester model has a direct correspondence with the differential equations that define the relationship among the elements of the dynamic systems.

D. *Lorentz Model*

In 1963 Lorentz abstracted three differential equations that can be used to test ideas in nonlinear dynamics. These equations are

$$\begin{aligned} \dot{x} &= \sigma(y-x) \\ \dot{y} &= -xz + rz - y \\ \dot{z} &= xy - bz \end{aligned} \tag{1}$$

This set of equations (Lorentz model) has been applied to the comprehension of complex processes, obtaining generic models to make continuous simulations, in particular related to complex production system behaviors. As a result, it allows identifying regulation mechanisms in the presence of disturbances. However, a system having such deterministic behavior may result unpredictable yielding chaotic solutions because of their sensitivity on initial conditions and settings of parameters σ, r and b. In particular, the Lorenz attractor is a set of chaotic solutions [7] of the Lorenz system which, when plotted, resemble a butterfly or figure eight, as depicted in Figs. …

Due to the nonlinear terms, (1) cannot be solved analytically. As an example, if we choose σ = 10; r = 28; b = 2.67, and initial conditions $x_0 = 0$; $y_0 = 1$; $z_0 = 0$, and solve using Euler´s numerical solution, for 50,000 iterations the three-dimensional plot is the same as that shown in Fig. 4, and its projection on planes XY, YZ, and XZ, is depicted in Fig. 5.

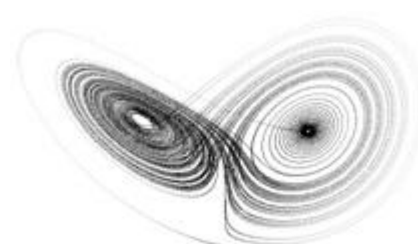

Figure 4. Lorentz attractor

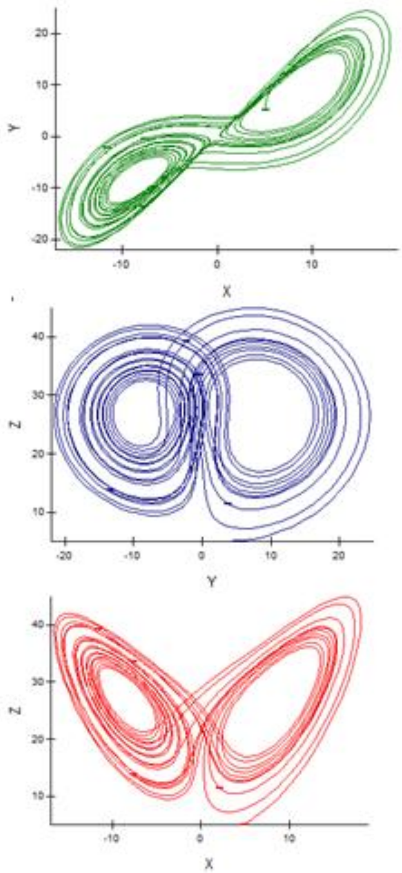

Figure 5. Lorentz chaotic attractors projections

$$
\begin{aligned}
\dot{x} &= 10(y-x) \\
\dot{y} &= -xz + 28z - y \\
\dot{z} &= xy - 2.67z
\end{aligned}
\tag{2}
$$

$$x_0 = 0;\ y_0 = 1;\ z_0 = 0$$

E. Client Mobile Device Interface

Whichever modeling tool is used (e.g., neural network, support vector machine, etc.), the process can be automated in a pervasive context. To that end, this design considers the use of a modern mobile communications platform, cloud computing, a mobile client device on-site by the plant, a monitoring platform inside or outside the mine, and a server in the cloud.

In the mobile client device, several software interfaces must be implemented to support the proposed solution [8]. An interface must be implemented for data transmission between the application server side in the private cloud and the M2M platform from the service provider [9]. This interface consists of two parts; one is to deploy a web service which provides local services for the remote M2M platform and is responsible for receiving real-time data from the Android client side; the other is to develop the service software which runs in the communication server background, with the functions of commands sending, data parsing, storage and query to the database. Two modules are considered; the first is to request services from the M2M platform, including platform login and sending command, and the second is the background processing of data which is called by local web service for parsing data and storing into the database. Another interface is responsible for getting data directly from plant sensors in the mine to the server in the cloud using the M2M infrastructure. Finally, a third interface must communicate any event, related to both mobile client and the plant inside the mine, to the screen at the monitoring and control platform.

F. Collecting Data and Request

From Fig. 1 we note that data from the plant's measurements are transmitted directly to the server in the cloud. In order to perform modeling and control over the plant, the process will be controlled by the operator, accessing the server in the cloud through the client program in the Android mobile device, allowing the operator in real-time, without leaving the site, to control the modeling process. Table 1 represents data from the plant inside the mine received by the server in the cloud. At this point no real data are collected, so they correspond to the solution of equation (2).

TABLE 1. COLLECTING DATA

Time (ms)	X	Y	Z
1	0	1	0
2	0.02	0.998	0
3	0.03956	0.997124	3.99E-05
…	…	…	…
1998	-8.493289	-8.793423	26.608915
1999	-8.499291	-8.799466	26.616371
2000	-8.505295	-8.805386	26.623996

G. Getting the Model

To identify and get a model for the plant's behavior, the operator using the application interface in the mobile client device asks the server to compute the model for the dynamic system under study (Fig. 6), specifying the modeling method.

The server will reply showing the requested model (Fig. 7). Several models can be tested until a suitable one is selected.

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H. Selecting the Mobile Client

According to Gartner's statistics, until November 2012 the market share of different operating systems for mobile devices was 72.4% for Android, 13.9% for iOS, 5.3% for Research In Motion, 3.0% for Bada, 2.6% for Symbian, 2.4% for Microsoft, and 0.4% for others.

Android is an operating system designed specifically for mobile devices [11]. It runs on the Linux kernel. The Android Software Development Kit (SDK) provides the tools and Application Programming Interfaces (APIs) necessary to develop applications using Java.

Applications written in Java can be compiled to be executed in a Dalvik virtual machine, which is a specialized virtual machine implementation designed for mobile device use. Other interesting characteristics of Android are the capability for reusing and replacing components, and the availability of a number of handset layouts, adaptable to larger, VGA, 2D graphics library, 3D graphics library based on OpenGL ES 1.0 specifications, and traditional Smartphone layouts.

Hence, to implement our mobile client we used Android because of its open nature, widespread use and the portability of the code.

I. Monitoring Platform Screen

During the entire process every event is displayed on a monitor screen (Fig. 8) at the control and monitoring platform, located either inside or outside the mine. The information displayed on the screen includes commands, data sent by the plant's real-time measurement system, request and replay messages between mobile client and server, numerical and graphical results from modeling, and real-time plant's response. These enable supervisors or other expert employees to supervise the automated control and tools from a remote operations centre.

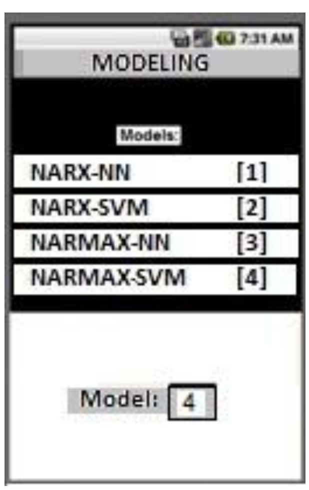

Figure 6. Android client interface

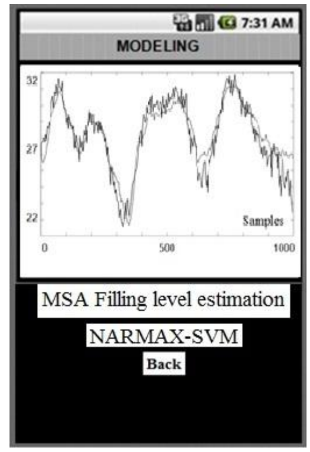

Figure 7. Model selection

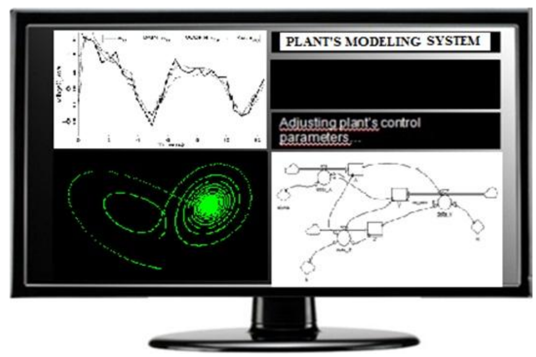

Figure 8. Monitoring screen

IV. MODELING APPLICATION

A. Software Sensor based on a NARMAX - Support Vector Machine Model for Semi-Autogenous Grinding

The estimation of states in complex processes such as the Semi-Autogenous Grinding process (SAG) in copper mining is an important and complex task due to difficulties in measuring some relevant variables directly online and in real time. In [12] the authors present interesting modeling results using Nonlinear Autoregressive Moving Average with Exogenous Input (NARMAX) and Support Vector Machines (SVM), when acting as estimators of state variables for a SAG milling operation. They propose a simple and original methodology to develop NARMAX models made with SVMs. In terms of the milling process, NARMAX-SVM provides a useful tool for estimating the value of the filling level parameter, which cannot be measured using readily available tools. The results show the predictive power of NARMAX-SVM models over those made of Neural Networks (NN). NARMAX-SVM has a significantly lower mean square error (MSE) than all other models.

The effective modeling results from NARMAX-SVM may be available to the operator through his mobile device,

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and for those on the monitoring platform as well as their mobiles devices anywhere inside the mine.

In what follows we will explain shortly how NARMAX-SVM works.

B. Virtual sensor structure

The application of virtual sensors to the SAG milling process described in [12] is to estimate on-line and in real time the values of the variable "Level". This is a significant variable for the grinding process, whose values are very difficult to measure directly, in real time and offline.

The NARX model (Fig. 9), proposed to implement the virtual sensors, uses as inputs the previous values of the variable "Level" (the one to be estimated), and an exogenous variable, the "Pressure on the mill shaft breaks". This is a variable easy to measure online and in real time, and is related to the variable of interest.

In the NARMAX model (Fig. 10), in addition to the same inputs used in the NARX model, the previous errors committed by the model are used.

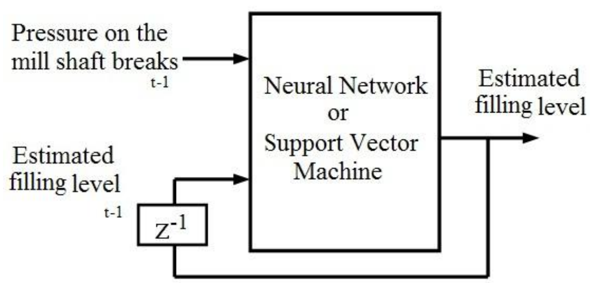

Figure 9. NARX virtual sensor structure

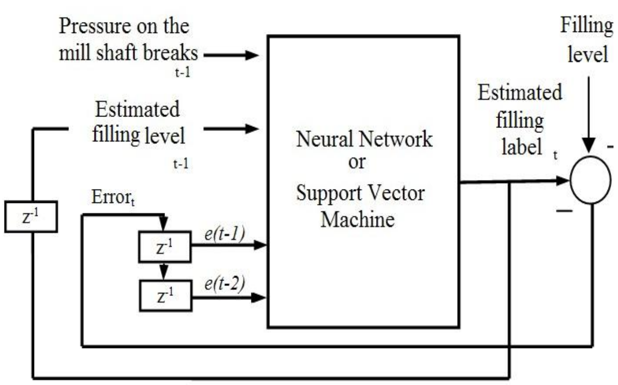

Figure 10. NARMAX virtual sensor structure

SVM and neural network models were trained with 500 samples and validated with 1000 samples. A third set of 1000 samples (test set) was used to get the final performance indices shown in Table 2. Each sample has the fill level and the pressure during breaks at time t-1 as inputs, and the filling level at time t as the output (the models are of first order).

Once identified, the four models obtained for estimating the filling level of the SAG mill (NARX and NARMAX using SVM and neural networks, respectively), their prediction capability for Multiple Step Ahead (MSA) forecast was evaluated. The estimation error was quantified using the mean square error (MSE) of Matlab. As a result, we can see that SVM implementations perform better than neural network cases.

TABLE 2. MSA FORECASTING MEAN SQUARE ERROR

	NARX	NARMAX
NN	3.5889	1.0773
SVM	1.0256	0.4424

D. Forecasting Results

Figs. 11 a) and b) show the estimation of the variable filling level (%) obtained with the NARX and NARMAX models, respectively, using SVM in MSA forecasting for the test data set.

From these results we can see that the NARMAX model performs better than NARX when both act as MSA predictors. NARMAX type models, though requiring a more complex identification procedure, consider previous prediction errors. Moreover, the models implemented using SVM significantly outperform those made using neural networks.

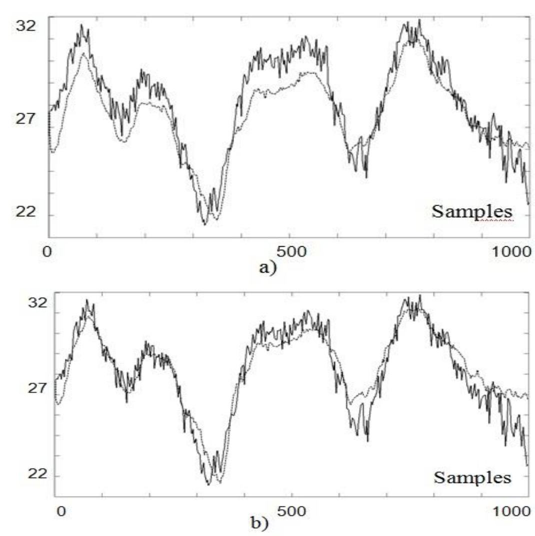

Figure 11. MSA Filling level estimation
a) NARX-SVM; b) NARMAX-SVM

V. CONCLUSIONS

This solution has advantages in many aspects. The machine-to-machine based communications mode with the server in the cloud and Android client inside the mine brings up pervasive mining, a system with wider coverage, higher communication efficiency, better fault-tolerance, and anytime anywhere availability.

This solution may be applied for any plant inside a mine for which their modeling in situ, in real time, allows to control aspects such as instability by adjusting their parameters without stopping the process.

In order to deploy the proposed design, this study has considered two modeling tools: NARX and NARMAX, which have been combined with Support Vector Machines (SVM) and Neural Networks (NN) to implement dynamic models. The purpose of the resulting models is to act as state estimators for the variable filling level of a semi-autogenous grinding process.

The proposed solution responds to the modeling needs, and also to the forecasting of plants functioning inside a mine. It simplifies the monitoring process and contributes to better control and enhanced safety.

The system proposed may represent a valuable design that helps to perform stricter supervision, set up safer work conditions for the miners, and deploy new technologies to enhance miner safety and improve processes inside the mine.

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REFERENCES

[1] N. Radio, Y. Zhang, M. Tatipamula, and V. Madisetti, «Next-Generation Applications on Cellular Networks: Trends, Challenges, and Solutions,» *Proceedings of the IEEE , vol.100, no.4*, pp. 841-854, 2012.

[2] E. Mancini, G. Wainer, K. Al-Zoubi, and O. Dalle, «Simulation in the Cloud Using Handheld Devices,» de *Cluster, Cloud and Grid Computing (CCGrid), 2012 12th IEEE/ACM International Symposium on*, pp. 867-872, 2012.

[3] S. Pocuca, D. Giljevic, «Machine to machine (M2M) communication impacts on mobile network capacity and behaviour,» de *MIPRO, 2012 Proceedings of the 35th International Convention* , pp. 607-611, 2012.

[4] F. Cubillos, G. Acuna, «Simulation Studies of On-Line Identification of Complex Processes with Neural Networks,» *Lecture Notes in Computer Science,Volume 3972*, pp. 808-814, 2006.

[5] I. Chairez, «Wavelet Differential Neural Network Observer,» *Transactions on Neural Networks*, pp. 1439-1449, 2009.

[6] K. Salahshoor, A. S. Kamalabady, «On-line Identification of Nonlinear Multivariable Processes using self-generating RBF Neural Networks,» *Asian Journal of Control, Vol. 12, No. 5*, pp. 626-639, 2010.

[7] M. D. Alfaro, J. M. Sepúlveda, and J. A. Ulloa, «Forecasting Chaotic Series in Manufacturing Systems by Vector Support Machine Regression and Neural Networks,» *International Journal of Computers Communications & Control*, pp. 8-17, 2012.

[8] Y. Yang, H. Ye, and S. Fei, «Design of communication interface for M2M-based positioning and monitoring system,» *Electronics, Communications and Control (ICECC)*, pp. 2624-2627, 9-11, 2011.

[9] W. Sun, M. Song, «A general M2M device model,» de *Web Society (SWS), 2010 IEEE 2nd Symposium*, pp. 578-581, 2010.

[10] C. Wang, W. Duan, J. Ma, and C. Wang, «The research of Android System Architecture and application programming,» *Computer Science and Network Technology (ICCSNT), 2011 International Conference on*, vol. 2, pp. 785 - 790, 2011.

[11] W. Hu, D. Han, A. Hindle, and K. Wong, «The build dependency perspective of Android's concrete architecture,» de *Mining Software Repositories (MSR), 2012 9th IEEE Working Conference on* , Zurich, Switzerland, pp. 128-131, 2012.

[12] G. Acuna, M. Curilem, and F. Cubillos, «Development of a Software Sensor based on a NARMAX-Support Vector Machine Model for Semi-Autogenous Grinding,» *Revista Iberoamericana de Automatica e Informatica Industrial*, p. unpublished, 2011.

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