Smart Home Resource Management based on Multi-Agent System Modeling Combined with SVM Machine Learning for Prediction and Decision-Making

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***Abstract*—The challenges of the Internet of Things (IoT) in a Smart Home are the monitoring of energy consumption and the automation of the household appliances connected to the Wireless Sensor Networks (WSN). The Smart Home monitoring technology has recently received great attention in the areas of IoT, home automation and WSN monitoring. Many companies seek to address a wide range of important issues including data mining and analysis, energy saving, comfort and security. The Smart Home application is inherently dynamic in the sense that it forms time-series data with real-time changing behavior. We seek to extract and analyze this incoming data to provide and predict useful features for the decision-making system in a Smart Home. This paper describes a new methodology of Smart Home data mining analysis based on Support Vector Machine (SVM) learning for a proposed Multi-Agent System (MAS). The key ideas are to represent the WSN behavior exchange by the modeled MAS, then to predict and classify features using the SVM regression model. Based on the cross-validation performed on the training data-set, the SVM model parameters are optimized for each combination of features. We demonstrate the validity of our methodology in the scenarios of emerging data recognition using a real "Smart Life" database.**

Keywords–Smart Home; distributed control; home automation; multi-agent systems; machine learning; support vector machine; time-series prediction.

I. INTRODUCTION

Nowadays, human beings always seek refuge, relaxation, security and prosperity at home, hence influencing the quality of life. The development of integrated electronic features to reduce costs has opened new perspectives of automation controls and monitoring of habitat that appears to be a task of great social importance. In the recent years, computer technology has been applied to the creation of Smart Homes in order to improve the lives of people at home. A Smart Home is an entity integrated with diversified automation, communication, and control service functions that collaborate in a convenient manner via intelligent tasks to provide many services, such as energy management, comfort, security and monitoring. The field of Smart Home is multidisciplinary with variations in architectures, dissimilar devices and systems, and diverse application and features [1]. In a Smart Home environment, the inter-operation unpredictability is one of the fundamental reasons behind uncertainty in the interoperability among these systems having diverse requirements, information exchanges and federated routine.

Home automation solutions range from overviewing information about energy consumption, presence and weather data in illustrative forms, automating and monitoring appliances either locally or remotely. Traditional strategies of building control are no longer efficient and smart to ensure the dynamic pricing of electricity and the demand response application for residential customers. To overcome this fundamental limitation and to solve such complex and dynamic decision processes, a Multi-Agent System (MAS) is required to provide intelligent energy management and home automation.

The MAS is a distributed artificial intelligence system that allows the intercommunication and the interaction between intelligent agents. The interactions of these entities of agent technology are made by the perception of the environment and by executing actions according to their decisions in order to conduct them and to study their varied situations. The agents must cooperate to achieve the overall goals as they have only a partial representation of their environment. The reactivity and pro-activity actions of the MAS are depicted by sensing and interpreting the changes in the environment in real-time [2].

Home automation can be addressed through the prediction and analysis of appliances' data, offering support for more advanced applications, such as activity recognition. The automatic human activity recognition requires new context-aware domestic smart services, such as controlling voice in Smart Home. Chahuara et al. [3] investigated an on-line activities of daily living recognition device from non-visual, audio and home automation sensors. The performances of this smart service were determined by comparing several learning models, such as hidden Markov model, the conditional random fields, the sequential Markov logic network, the Support Vector Machine (SVM), the random forest and the non-sequential Markov logic network.

Predicted time-series data can be investigated for energy consumption data mining, home automation and also home-owner activity and behavior forecasting. Data history clusters are utilized by machine learning, which take into account the effects of the previous device states. Therefore, we propose a MAS using the SVM approach to predict and classify

 ISBN: 978-1-61208-616-3

features. Currently, Smart Home owners have trouble to daily control and manage the various heterogeneous smart sensors and devices. One of the greatest challenges in the current Smart Home field is to deal with the collaborative control problem of these heterogeneous smart devices using a home automation platform.

Our contribution is to propose a universal Smart Home automation platform architecture based on a multi-agent system and predictive software for decision making. The proposed system provides heterogeneous devices' connectivity, collaborative agents' communication, human-devices' interaction and appliances' auto-control to improve the Smart Home automation system. In this paper, we represent the ability to predict the behavior of Smart Home owners by monitoring the daily appliances' usages. Indeed, we develop a robust, flexible and intelligent platform integrating temporal contextual information based on the incoming sensor data. The developed prototype is used to forecast daily power consumption and to estimate human actions in a Smart Home. We test the performance of our system using statistical metrics, and the experimental results are encouraging. The model features are updated based on the time series analysis.

The MASs consist of an intelligent distributed artificial system integrating Internet of Things (IoT) aspects and human cognition for Smart Home automation. The proposed architecture is based on a virtual multi-agent platform incorporating services to provide Wireless Sensor Networks (WSN) interconnectivity. This design makes it possible for Smart Homes to include organizational aspects of human activities, improving the auto-control and auto-programming of appliances. The autonomous agents fixed in devices consume and provide different services to offer more distributed and complex functionalities and capabilities.

The proposed MAS should guarantee the platform scalability, and flexibility and efficient and intelligent communication with the ability to add new functionalities for the layer of user applications. The main functions are the fusion of incoming information from heterogeneous sources. The suggested system must be able to monitor automatically the Smart Home and to predict the household energy consumption through a predictive model with input variables regarding the weather and space information, appliances' state, power consumption and the time. The WSNs are used to analyze the command of electrical appliances and the interactions between different sensors in order to automatically make decisions on a daily basis.

The rest of the sections of this paper are structured as follows. Section II describes the system architecture overview of the proposed system modeling for home automation. Section III defines the predicting incoming time-sequence data models. We explain the experiments and results by considering the proposed method in Section IV. Section V presents the conclusion and some future work.

II. Related Work

A Smart Home should meet the requirements of homeowners, including security, weather information, consumption measurements and remote control of different categories of smart products. According to the rapid anticipation for the Smart Home, several commercial intelligent IoT solutions are involved for home automation using smart sensors as a universal remote-control software-defined Smart Home appliance that can be handled safely by homeowners [4].

Smart Home applications are generally based on the IoT and cognitive dynamic systems. Feng et al. [5] investigated a cognitive interactive people-centric IoT in the Smart Home to improve human life quality with intelligent control of its setting by considering perception actions that would contribute to the interactive IoT ecosystem.

Viswanath et al. [6] proposed the design of an IoT system for real-time residential smart grid applications focused on a large number of home devices communicating through a universal IoT home gateway, a cloud back-end server, and user interfaces offering services as well as energy management, demand response management, dynamic pricing, energy monitoring, home automation and home security.

The MASs are a preferred approach addressing complex systems that rely on classical artificial intelligence extended to a distributed computing environment and the sharing of tasks, resources and knowledge. Their totally decentralized nature makes them particularly suitable for this type of systems. The MASs allow working on the overall operation of a system by focusing on the component entities and their interactions. However, MASs are applied increasingly in various fields of real life due to the technological revolution and the intensive use of Internet services by large companies. Several constraints are questioned because of this application domain diversity. Among these constraints we can cite the difficulty of specifying and systematically modeling applications, the problems related to the concepts of resource allocations and the complexity of negotiation and inter-cooperation between agents.

Several researches identify information security requirements that impact critical societal services ranging over transport, home automation, energy management, industrial control, and health services and their perceptions and attitudes on the IoT security [7]. The fields of telecommunications and information may also be based on MASs for network management, remote management of Smart Home and information knowledge. In industry, the MASs are operated in production automation processes, smart cards and cooperative robots. Manufacturers often try to achieve the effective resolution of issues targeted as the complexity of real-mode systems. These issues provide an intellectual challenge to researchers who seek to maintain soft constraint systems using agents. Thus, realizing the integration of control, maintenance and technical management of automation system based on MASs can lead to the resolution of the various industrial problems. Recently, the MASs are utilized for crop irrigation monitoring allowing farmers to rationalize the amount of resources that optimize crop needs. The system offeres an economical solution combining intelligence and context-awareness by merging heterogeneous data from the WSNs [8]. Tele-medicine also applies MASs in the supervision and assistance of the elderly sick. They are obviously used in the field of logistics and information on trips [9].

Smart grid architectures consist of many autonomous systems with partial knowledge that have to cooperate and communicate in order to solve complex problems. The MAS is a mature and efficient mechanism that provides many features imperatively required for smart grid applications to solve their distributed nature problems. However, it is still difficult to provide a generic perspective on smart grid architectures. Dynamical MASs have been used for the systematic modeling of the cyber and electrical grids to provide flexibility. Other solutions for smart grid architectures have been explored using a MAS to develop a decision-making support for distributed power generation [10] and for managing electric vehicles' charging stations [11]. Sun et al. [12] proposed a multi-agent system framework for home automation, based on belief, desire and intention model for an agent individual behavior design, a regulation policy-based multi-agent collaboration behavior design and a Petri-net method for system analysis and evaluation.

As dynamic contributors to smart grids, Smart Home systems have ensured interactive communication that affects the electricity demand, generation, and bills, leading to a reduction in the total demand curve. Smart Grid modeling is based on a multi-agent system that designs each Smart Home as an autonomous agent making rational decisions for power generation, storage, and trading features founded on the expected utilities they offer. The individual decisions of these home agents significantly reduce electricity costs, which encourages conventional homes to purchase their own local generation-storage systems and to benefit from the different operational conditions.

Integrating the IoT with Cloud computing and Web services, Javed et al. [13] investigated model-based wireless sensor nodes for Smart Home monitoring and HVAC using machine learning like the artificial neural network to estimate setpoints for controlling the heating, ventilation, and cooling of the Smart Home while reducing human intervention.

The energy consumption cost reduction requires a dynamic demand response and distributed energy resource management. Therefore, home automation trends towards IoT and ambient intelligence technologies for device self-control. Ruta, et al. [14] put forward a distributed multi-agent framework for home and building automation and energy management, based on a semantic improvement of domotic standards using the discovery and orchestration of formal annotation-based resources to support the semantic characterization of user profiles and device functionalities. In [15], the authors suggested an adapting automation architecture for activity recognition in Smart Home based on semi-supervised learning algorithms and Markov models combining the data observations and the feedback of users decisions. Jose et al. [16] studied the various security issues and verification approaches to improve Smart Home security. They proposed a device fingerprinting algorithm that considered the device's geographical location, username and password of utilizers as well as the device used to access the home.

III. Multi-Agents System Modeling For Home Automation

Using an agent language like Java Agent Development (JADE) framework, the MASs are able to share information, to exchange messages and to solve complex problems. The JADE is a software framework fully implemented in Java language to simplify the development of the MAS using graphical tools for debugging and deployment according to the Foundation for Intelligent Physical Agents (FIPA) standard and the Agent Communication Language (FIPA-ACL) specifications [17]. The FIPA interaction protocols between agents are being developed to define a standard communication structure ensuring the conduct of conversations between these agents. These protocols use a manager agent to offer the performance of a task in terms of appropriate resources and expertise by selecting the best proposal returned and then begins the necessary exchanges with the elected official. An agent asks another agent to perform an action and inform the initiator about the structure in which agents exist and operate [18].

A. Agents Functionalities

In the MAS-based Smart Home setting, we use four containers where each container is a room of the house embedded in a main container (Smart Home container) as shown in Figure 1. These containers interact to estimate the presence of owners and their provided activity in each Smart Home room. Every container consists of a set of agents instances' that represent the equipment or environment variables (temperature, humidity, etc.) responsible for learning the habits, equipment states, environmental conditions and situations of the home owners in order to supervise, control and take appropriate actions. Each agent has a specific role. The proposed MAS

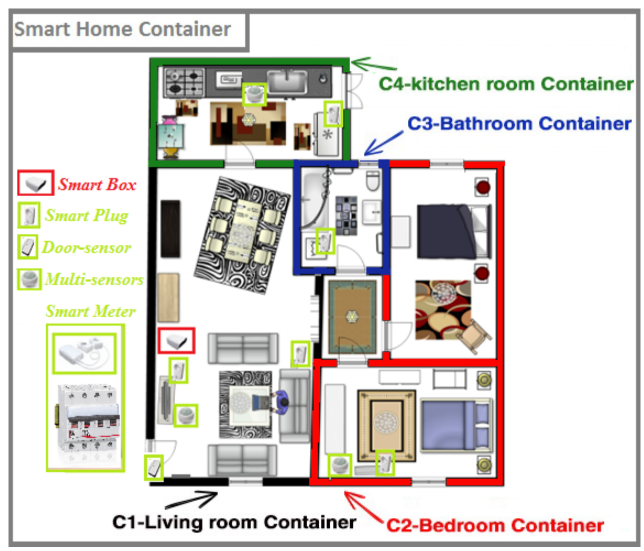

Figure 1. General framework for a Smart Home system

architecture for each container is presented in Figure 2. The architecture is a hierarchical MAS consisting of eight agent groups constituting the objects of a container that meet their goals through the collaboration with other containers (agent groups). The specific roles of agents forming the MAS system consist of:

- "Sensor Agent": This agent is responsible for monitoring and controlling environment sensors by receiving messages from the same container agents and saving them in the database. These messages can be transmitted to the "Electrical Outlet Agent", the "Air Conditioner Agent" and the "Lamp Agent" in order to predict the user actions.
- "Electrical Outlet Agent": This agent receives the data sent by the "Sensor Agent" and uses it as an input of

 ISBN: 978-1-61208-616-3

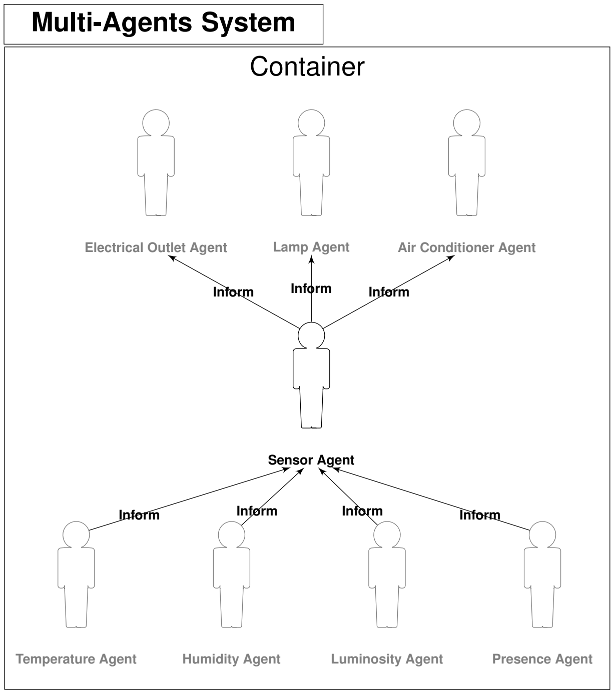

Figure 2. Proposed MAS-based architecture for Smart Home automation

the SVM classifier to predict the decision states of the electrical outlet.

- "Air Conditioner Agent": The following agent receives the data sent by the "Sensor Agent" and uses it as an input of the SVM classifier to predict the states of the air conditioner.
- "Lamp Agent": The required data to predict the states of the lamp are sent by the "Sensor Agent". The "Lamp Agent" uses this information as an input of the SVM classifier.
- "Temperature Agent": It treats the prediction of the temperature variable for a defined period using the SVM machine learning. Then, the results are sent to the "Sensor Agent" embedded in the same container.
- "Humidity Agent": It predicts the humidity variable for a defined period using the SVM machine learning. The results are sent to the "Sensor Agent" embedded in the same container.
- "Luminosity Agent": It predicts the luminosity variable for a defined period using the SVM machine learning. The results are sent to the "Sensor Agent" embedded in the same container.
- "Presence Agent": It predicts the presence state for a defined period using the SVM machine learning. The results are sent to the "Sensor Agent" embedded in the same container.

IV. PREDICTING INCOMING TIME-SEQUENCE DATA MODEL

A. SVM model for prediction and making-decision

In order to predict and classify the measured results, numerous methods are applied. The SVM method seems to be better suited to this problem saw his ability to handle a small amount of data. The SVM models have been widely used to solve classification and regression problems.

1) Classification function: The SVM separates the different classes of data, by a hyperplane corresponding to the following decision function:

$$f(\mathbf{x}) = sign(\langle \mathbf{w}, \phi(\mathbf{x}) \rangle + b) \tag{1}$$

where **x** is a set of observations, **w** is the vector of coefficients and b is a noise constant.
This supervised machine learning seeks to deduce the function $\Phi : \mathbf{x} \subset \Re^d \rightarrow \{-1; 1\}$ from a set of observations that will correctly classify a maximum number of vectors $\mathbf{x}_i$ by describing the optimal hyper-plane between the two classes:
Considering two classes of points, scored -1 and 1, we have a set of N vectors $\mathbf{x}_i \in \mathbf{X} \subset \Re^d, i \in [1, N]$ (d is the input space dimension) with their associated class $y_i \in \{-1; 1\}$.
The constrained quadratic optimization problem can be solved by $\mathbf{w} = \sum_i \alpha_i \Phi(\mathbf{x}_i)$ in terms of a subset of training patterns N. The classifier capacity results in the assignment of a new unknown point in the right class.
The classification function is given by the minimum of the following function:

$$f < \mathbf{w}, \xi >= \min \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_i (\xi_i) \tag{2}$$

subject to:

$$y_i(\langle \mathbf{w}, \Phi(\mathbf{x}_i) + b) \geq 1 - \xi_i \rangle$$

$$\xi_i \geq 0$$

where C is a pre-specified value, and ξ_i are the class variables. Due to the rich theoretical bases and the possibility of transferring the problem to a large space of features, the SVM can provide a good generalization performance. The sensors send pairs of values and activities forming the training set.
This nonlinear binary classification problem requires a maximum optimization model based on the Lagrange multipliers technique and the Kernel function. The SVM classifier manages its nonlinear nature by replacing each scalar product of the weight of activities in a dual form with the Kernel function. The SVM solution **w** can be shown using the kernel method as follows:

$$\mathbf{w} = \sum_i y_i \alpha_i \Phi(\mathbf{x}_i)$$

The support vectors' coefficients occur when a point $(\mathbf{x}_i, y_i)$ meets the constraint found by minimizing the following equation:

$$\mathbf{W}(\alpha) = \sum \sum_{j=1} \alpha_i - \frac{1}{2} \sum_{i=1} \sum_{j=1} (\alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j)) \tag{3}$$

subject to:

$$0 \leq \alpha_i \leq C$$

$$\sum_i y_i \alpha_i = 0$$

2) Regression function: When the SVM are used in regression problems to predict real values, we will talk about the "Support Vector Regression" (SVR) technique. Let consider all of training points $(\mathbf{x}_1, y_1)...(\mathbf{x}_N, y_N)$ where $\mathbf{x}_i \in \mathbf{X} \subset \Re^d, i \in [1, N]$ and the output target $y_i \in \mathbf{Y} \subset \Re^1, i \in [1, N]$, with the condition $C \succ 0$ and $\epsilon \succ 0$. The SVR can also perform regression and estimate the accuracy by computing the scale parameter $\mathbf{y} = f(\mathbf{x})$, where f($\mathbf{x}$) is the estimated decision function. This function ignores errors that are smaller than a certain threshold $\epsilon \succ 0$, thus creating a tube around the true output. The optimal regression function of the two subjects

$$\langle \mathbf{w}, \Phi(\mathbf{x}_i) \rangle + b - y_i \leq \epsilon - \xi^-$$
$$y_i - \langle w, \Phi(x_i) \rangle + b \leq \epsilon - \xi^+$$

is given by:

$$f < W, \xi >= \min \frac{1}{2} \|w\|^2 + C \sum_i (\xi_i^-) + C \sum_i (\xi_i^+) \quad (4)$$

where C is a pre-specified value, and ξ_i^-, ξ_i^+ are gap variables representing upper and lower constraints on system outputs. The dual form of SVR using the Kernel function is:

$$\max_{\alpha,\alpha^*} W(\alpha, \alpha^*) = \max_{\alpha,\alpha^*} \sum_{i=1} \alpha_i^*(y_i - \epsilon) - \alpha_i(y_i + \epsilon)$$
$$-\frac{1}{2} \sum_{i=1} \sum_{j=1}^{l} (\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j) K(x_i, x_j) \quad (5)$$

with $\sum_{i=1}(\alpha_i^* - \alpha_i) = 0$ et $0 \leq \alpha_i, \alpha_i^* \leq C$.
The result regression function of the resolution of the above equation by determining the Lagrange multipliers α_i, α_i^* is given by:

$$f(x) = \sum_{SVs} (\bar{\alpha}_i - \bar{\alpha_i^*}) K(x_i, x_j + \bar{b}) \quad (6)$$

with:

$$\bar{b} = -\frac{1}{2} \sum_{i=1}^{l} (\alpha_i - \alpha_i^*)(K(x_i, x_r) + K(x_i, x_s)) \quad (7)$$

$$< \bar{w}, x >= \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(x_i, x_j) \quad (8)$$

Our research provides the opportunity to learn the behavior of a resident of a Smart Home from all detected usual tasks. The appropriate equipment, according to the "Electrical Outlet Agent", the "Air Conditioner Agent" and the "Lamp Agent", request the "Sensor Agent" to look for specific data to select the equipment criteria grouped by the "Temperature Agent", the "Humidity Agent", the "Luminosity Agent" and the "Presence Agent". The "Sensor Agent" returns the requested list which will be processed by the equipment agents. Finally, the results that meet the needs of the resident return to the "Sensor Agent". The interactions between agents performing the learning algorithm are illustrated by sequence diagrams shown in Figures 3 and 4.

After making its predictions, the MAS sends notifications

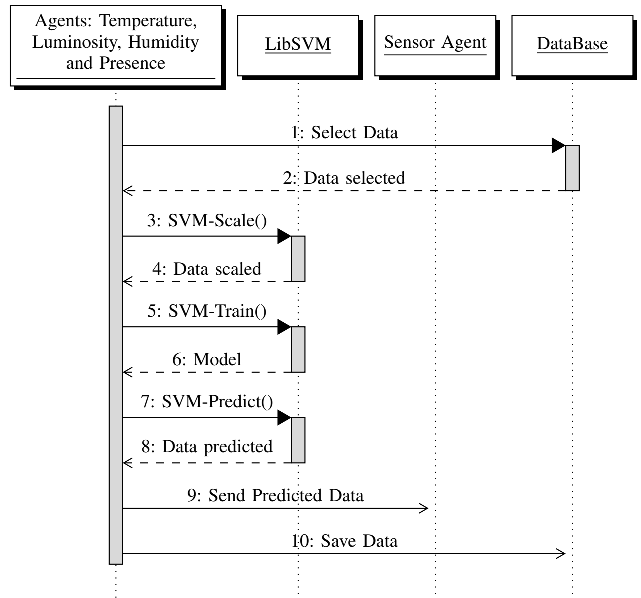

Figure 3. Interaction sequence diagram for temperature, luminosity, humidity and presence agents

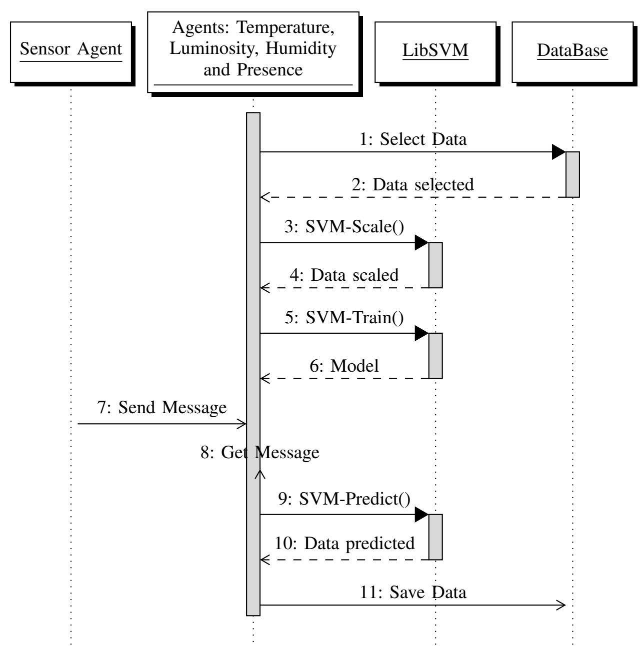

Figure 4. Interaction sequence diagram for Sensor Agent

to the user who can consult the list of predicted tasks. Following its consulted results, the user can react by canceling, confirming or changing the date and the system will finally save these changes.

B. Quality and precision criteria

To assess the quality of our models, we will mainly look at their respective predictive performances measured by the Mean Squared Error (MSE). As a matter of fact, we are working with hourly-normalized data and we will model each hour independently from one another, which is a common choice given the type of data, hence leading to a model of 24 separate daily hours. Indexing the respective MSE criteria of these models by the instant $i = 0, ..., 23$, to which they are associated, and given their respective observations $y_1, i, ..., y_N$,i, these models return 24 t-day-ahead predictions, defined as the expectations of the predictive distributions, i.e., for $i = 0, .., 23$:

$$\mathbf{x} = \frac{1}{N} \sum_{i=1}^{N} (\hat{y}_i y_i)^2 \tag{9}$$

In our case study, we managed to set up a training set of three months in 2015 so as to predict the values of the different variables for June 2016.

V. Experiments and Results

The features are obtained from the WSN installed in the Smart Home. These features are classified using the SVM machine learning. The development of the classifier takes place using the LIBSVM library of the framework JADE. The LIBSVM toolbox generates a structure containing the type of the SVM, the kernel type, the number of support vectors, the number of classes, the class labels and the offset. It is employed both in the training and testing phases. Several SVM structures are trained on all the possible combinations of signals. A prediction can be obtained with a combination of previously predicted signals.
In our case study, the SVM machine learning is made in four steps (LIBSVM functions):

1) "SVM-Scale" function for data normalization.
2) "SVM-Train" function for training data to obtain a prediction model.
3) "SVM-Predict" function using the model to make predictions about the classes or the values in the case of regression.
4) "SVM-Test" function to calculate the model performance. In this step, we select the data whose class or values are known (for regression) and we use the model to predict their class and value, and in the end, we compare the two real and predicted classes (or the real and predicted values). To assess the quality of the predictions obtained in the "SVM-Test", the MSE is used as a measure of a prediction error.

We choose to use as "Input-Attributes" the time and the date and as "Input-Labels" the class or the regression values for the prediction of power consumption, presence, open/close and environment variables (temperature, humidity and luminosity). The SVM model parameters are specified in Table I. We construct an SVM learning scheme to predict the environment variables and power consumption in a Smart Home. We use the "Smart Life" datasets for validating the performance of our proposed architectures. The "Smart Life" datasets consists of independent datasets collected from a couple of apartments for a year using different sensors. The sensors are installed in everyday objects, such as refrigerator, and light switches, etc. We thoroughly analyze a full year historical data and utilize them to configure a large number of input and output datasets for the SVM learning. The proposed SVM-based prediction model can simultaneously predict the future amount of time-series data. Throughout the experiments, the proposed SVM-based prediction model shows the highest prediction accuracy, compared to other prediction models, such as the conventional time-series and the artificial neural network models. As a result, these prediction data can be effectively utilized for behavior recognition and energy management systems in Smart Home.

Using the MSE function to calculate the performance of the SVM predictor, we show in Figure 5 and Figure 6 that the prediction for the time series with low intensity of harmonic variations, as the temperature variable ($MSE = 8.57$), is more performant than the high intensity of harmonic variations, like the humidity variable ($MSE = 18.6948$). The Performance of the SVM model for the air conditioners' operating status regression is perfect with an $MSEvalue = 0.57$, describing the conformity of the predicted equipment state values to the real ones. These simulations confirm the performance of the SVM predictor, compared with the real values, as shown in Figure 7.
We propose the SVM machine learning to automate the

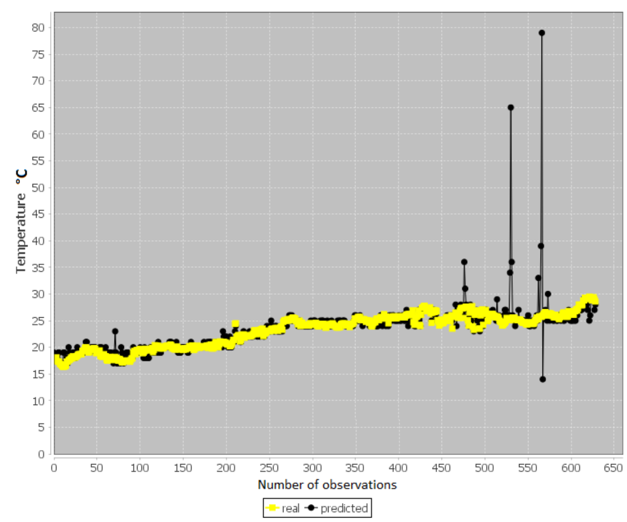

Figure 5. Performance of SVM model for temperature prediction (MSE= 8.57)

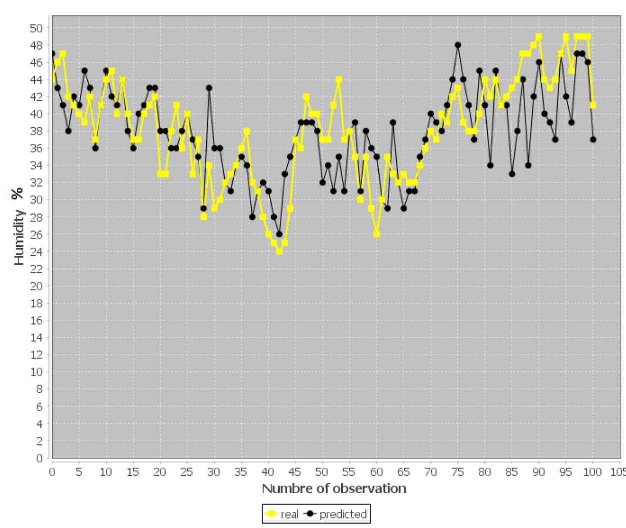

Figure 6. Performance of SVM model for humidity prediction (MSE= 18.6948)

TABLE I. SVM MODEL PARAMETERS FOR EACH VARIABLE

			State	Presence	Door-sensor	Temperature	Humidity	Luminosity	Power
SVM-Train	**Inputs**	***Attributes***	Hour	Hour	Hour	Hour	Hour	Hour	Hour
			Minute	Minute	Minute	Minute	Minute	Minute	Minute
			Day of the month	Day of the month	Day of the month	Day of the month	Day of the month	Day of the month	Day of the month
			Day of the week	Day of the week	Day of the week	Day of the week	Day of the week	Day of the week	Day of the week
			Week of the month	Week of the month	Week of the month	Week of the month	Week of the month	Week of the month	Week of the month
			Month	Month	Month	Month	Month	Month	Month
			Year	Year	Year	Year	Year	Year	Year
		Labels	Class '0' : OFF	Class '0' : Absence	Class '0' : Close	Real values	Real values	Real values	Real Values
			Class '1' : ON	Class '1' : Presence	Class '1' : Open				
	Outputs	***Model***	Regression Model	Regression	Regression	Classification	Classification	Classification	Classification
SVM-Predict	**Inputs**	***Attributes***	Hour	Hour	Hour	Hour	Hour	Hour	Hour
			Minute	Minute	Minute	Minute	Minute	Minute	Minute
			Day of the month	Day of the month	Day of the month	Day of the month	Day of the month	Day of the month	Day of the month
			Day of the week	Day of the week	Day of the week	Day of the week	Day of the week	Day of the week	Day of the week
			Week of the month	Week of the month	Week of the month	Week of the month	Week of the month	Week of the month	Week of the month
			Month	Month	Month	Month	Month	Month	Month
			Year	Year	Year	Year	Year	Year	Year
	Outputs	***Labels***	Class '0' : OFF	Class '0' : Absence	Class '0' : Close	Real values	Real values	Real values	Real Values
			Class '1' : ON	Class '1' : Presence	Class '1' : Open				
SVM-Test	**Inputs**	**Attributes**	Hour	Hour	Hour	Hour	Hour	Hour	Hour
			Minute	Minute	Minute	Minute	Minute	Minute	Minute
			Day of the month	Day of the month	Day of the month	Day of the month	Day of the month	Day of the month	Day of the month
			Day of the week	Day of the week	Day of the week	Day of the week	Day of the week	Day of the week	Day of the week
			Week of the month	Week of the month	Week of the month	Week of the month	Week of the month	Week of the month	Week of the month
			Month	Month	Month	Month	Month	Month	Month
			Year	Year	Year	Year	Year	Year	Year
		Labels	Class '0' : OFF	Class '0' : Absence	Class '0' : Close	Real values	Real values	Real values	Real Values
			Class '1' : ON	Class '1' : Presence	Class '1' : Open				
	Outputs	***Performance***	MSE	MSE	MSE	MSE	MSE	MSE	MSE

process of air conditioning in a home as a case study. We use the SVM machine learning to predict the ambient temperature and the condition and value of the power of the air conditioner at a specific date-time. These recorded features will be useful for the decision-making and automatic control of the air conditioner. The SVM classifier determines the temperature set point belonging to a predefined regression class. The experimental results on the real world application "Smart Life" demonstrate the effectiveness of our approach in case of linear classification and regression. The SVM model has a remarkable learning ability in a distributed intelligence system.

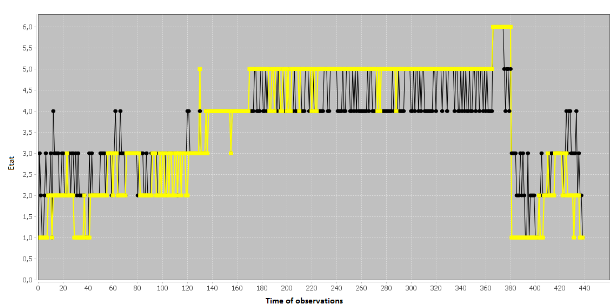

Figure 7. Performance of SVM model for air conditioner operating state regression (MSE= 0.57)

VI. Conclusion and Future Work

In this paper, we have started by introducing the IoT and the MASs and their applications to design our MAS architecture for Smart Home automation. Indeed, we have proposed a new active learning algorithm based on the SVM approach adopted to solve the problem of prediction and multi-class classification of WSN devices installed in a Smart Home. The technical experience requires to manipulate the proposed Smart Home scenario with the machine learning algorithm, the MAS system and the Android mobile system. Our solution must be well integrated into the professional company IoT application. For future work, we will use a hybrid algorithm combining the hiden Markov model and the SVM model for features' prediction and the decision tree model for making decision to remotely control intelligent households via an Android application. Nevertheless, we can extend the realization of this project by enriching the use of more accurate intelligent sensors. In addition, we can optimize our solution using a consistent big-data learning base for real-time prediction of sequential data.

Acknowledgment

This work is part of a PhD thesis supported by "PASRI-MOBIDOC" Project financed by the EU, "Chifco" company, "Innov'COM" laboratory, and National School of Engineering of Tunis-ENIT.

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