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Context-aware framework for energy management system

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***Abstract*— *In this work we present a context-aware framework for energy management system (CAEMS). The CAEMS is a context awareness framework that aims to provide a comprehensive solution to reason about the context from the level of sensor data to the high-level situation awareness (actuator or devices). The paper describes these challenges and presents data management solutions as a module of context data analysis for the energy (Microgrid) control system. These solutions include sensor data acquisition and time series forecasting, ontology model and context prediction model for analytical query processing past and future context data.*

Keywords*— *context prediction, ontology, sensor data acquisition, energy system.

I. Introduction

An energy system (such like Microgrid) includes medium- and/or low-voltage distribution systems with distributed energy sources, storage devices, and controllable loads and of course with some control system which allows integrating all of them. They can operate either if connected to the main power network or if isolated in a controlled and coordinated way [1, 2]. The energy system has to integrate and support energy, communication, and information or management levels. Control regulation has to connect parameters on the energy level and on the user comfort level. In the management system factors influencing the decision-making are context parameters [3]. Context can be defined as any information that used to characterize the situation of an entity, where the entity is a person, place, or some energy values.

Context-awareness energy management paradigm focuses on availability and graceful integration of computing and energy technologies. The CAEMS is multiagent and intelligent information system which involves the information from different heterogeneous sources, such as alternative power sources, a large number of sensors, power converters and processing devices, actuators that solve critical user tasks that are in different locations or zones (buildings or groups of buildings). The CAEMS builds on context approach as context awareness and situation awareness of the system. Integration of information, obtained from heterogeneous sources, into the context produces a model of the current state of the real object, as well as reduces the amount of data to be processed, on the basis of which the control algorithms can generate numerous control solutions.

II. CAEMS Framework

The CAEMS integration allows both to control energy resources and to take into account the wishes of the user [4].

The energy system represented on basid Paradigm of interacting power equipment and solving such tasks:

1) Generation: Renewable energy integration.
2) Multi-directional power flow.
3) Reducing the peak load leveling and load demand.
4) The two-way exchange of energy with the system.
5) Limiting short-circuit and providing the required quality of electricity.
6) Uninterrupted power supply.

The tasks on power level solved by intelligent management Paradigm:

1) Enhanced situational awareness.
2) Operation based on real-time data.
3) Collect data from the measuring devices.
4) Calculate supply and demand of power.
5) Predictive capability to prevent emergencies [5].

After analysis of energy system paradigm and challenges for intelligent management, we have to decided that it is important to solve tasks which allow creating a CAEMS that will be able to forecast and react smartly to the actions of all electrical facilities (loads and generators) connected to energy system, by means of converters in the unified information environment.

The main tasks of CAEMS:

1) Create the general approaches to the context prediction.
2) Create and support automated decision-making approaches for reasoning context for energy consumption and user comfort.

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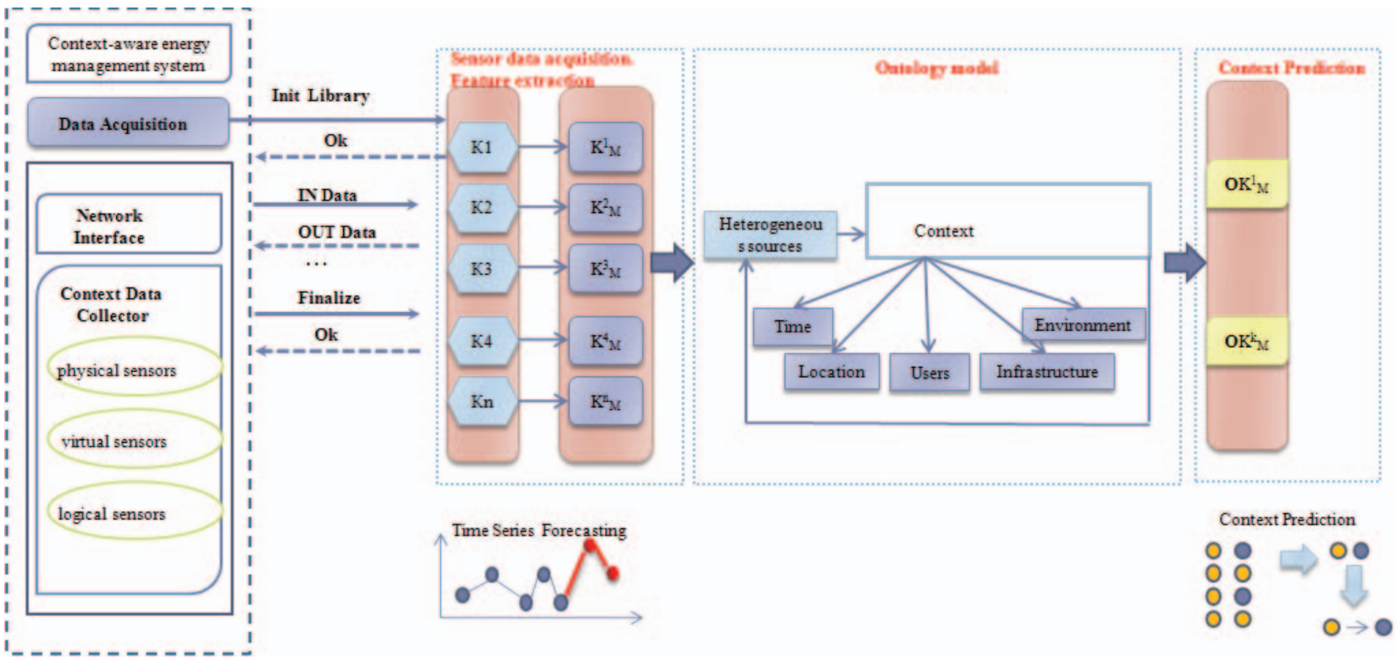

Fig.1. Context-aware framework for energy management system.

The energy system is highly distributed, and CAEMS has to manage large amounts of energy-related data and has to be able to react rapidly and smartly when conditions change and for this task we use smoothies and predictive techniques for data from sensors.

Sensors are the devices that directly measure the environment characteristics (e.g. temperature, light, humidity, power etc.). Sensors can as well be virtual (e.g. user preferences).

Context-aware management process consists of several steps:

- *Sensor data acquisition.* This step takes data received from multiple sensors and arranges them into the vector of values.
- *Feature extraction.* This step transforms raw sensor data for further usage. The vector of features is formed from a vector of sensor data.
- *Ontology model.* This is the step that involves user interaction. The frequency of involvement depends on a quality of prediction step if classes of ontology are often overwritten and replaced that will result in more frequent user involvements.
- *Context prediction*. This step takes the history of class vectors and estimates a future expected class membership vector.

III. SENSOR DATA ACQUISITION. FEATURE EXTRACTION.

Context prediction requires the consideration of the preliminary time series processing consists in the detection of the series values anomalous values and series smoothing. The randomness of the commutation, though, leads to the disturbances in power consumption characteristics. Keeping a record of time points and the value of the disturbances complicates the forecasting process and can lead to erroneous results. Filtration or smoothing of context time series is the necessary preliminary prediction stage for obtaining trends. Thus, the first step of the module of context data analysis is the filtration and the second step is the prediction [6-8]. There are three distinct groups of smoothing:

1) Averaging Methods – moving average, weighted moving average;

2) Exponential Smoothing Methods – simple, weighted, exponential, double;

3) Kalman filter.

And three group of prediction:

1) Interpolation – linear, polynomial, spline;

2) Extrapolation – linear, polynomial, French curve, conic;

3) Linear prediction.

Table 1 consists of the lists initial parameters for prediction algorithms.

TABLE I. PARAMETERS FOR FORECASTING ALGORITHMS

No.	Letter symbol	Description
1	γ	The number of series values to be forecasted
2	t_{max}	The right margin of the time series forecasting interval
3	n	Sample (a number of time series values, used for a single forecasting)
4	t_k	Initial time point of the forecasting
5	n_{min}	Minimal sample value
6	n_{max}	Maximal sample value

Forecasting of the time series without noise is carried out by the following algorithm:

1) Assigning γ, n and n values;

2) Reading the value of a current time series value $X(t_k)$. If $t_k = t_{max}$ - algorithm stops;

3) If $t_k<t_{max}$, for the current time series value at a time point t_k the task of single forecasting on the interval γ is solved. Predicted time series value will be $Y(t_k+\gamma)$ as in (1)

$$E(t) = Y(t_k + \gamma) - X(t_k). \qquad (1)$$

4) $Y(t_k+\gamma)$ is entered in the dynamic list of the time series values being predicted on the interval up to t_{max}.

5) If $t_k<t_{max}$, k=k+1 and the dynamic list of the time series values being predicted is checked for an element with a $X(t_k+\gamma)$. If there is such an element, where $Q(t_k+\gamma)$ is a root-mean-square error (RMSE) of a time series values being predicted from the real timestamp $X(t_k+\gamma)$ as in (2)

$$Q(t_k + \gamma) = M\left[E^2(t)\right] = M\left[(Y(t_k + \gamma) - X(t_k + \gamma))^2\right]. \qquad (2)$$

Sample n regularizing is performed and the element $Y(t_k+\gamma)$ is deleted from the dynamic list of the time series values being predicted. If the list doesn`t contain an element with a timestamp t_k, the algorithm goes to step 2).

The algorithm repeats itself until forecasting error value won`t be received for every time series value on the time interval up to t_{max}.

If the value $Q(t_k+\gamma)$ falls outside the confidence range of prediction errors, the task of regularizing sample *n* of the prediction method is performed. By sample regularizing we understand sample value alteration up to the value which provides the transition of $Q(t_k+\gamma)$ to the area of confidence range.

6) Assign $n=n_{min}$, n_{max}=max;

7) Read the RMSE $Q(t_k+\gamma)$ from a dynamic list of time series being forecasting $Q(t_{k-1}+\gamma)$. The find unacceptable values of time series we used Irwin criterion as in (3):

$$\lambda(t_k + \gamma) = \mid Q(t_k + \gamma) - \mid Q(t_{k-1} + \gamma) \mid / \mid Q(t_k + \gamma) \mid . \qquad (3)$$

8) If $n < n_{max}$, then n=n+1 and algorithm goes to step 2).

This approach with the regularizing sample, it is an important step in enabling the processing of larger amounts of heterogeneous data from distributed and renewable energy sources into the energy system.

Figure 2 shows an example of the result of the French curve extrapolation and the RMSE of the time series without model regularization.

Figure 3 shows an example of the result of the proposed module regularization depending on the values of the time series (acceptable or unacceptable values). Based on the optimization of the sample size, changes the order of the polynomial of the prediction time series method.

The proposed approach of regularization (adaptation) of time series for forecasting method allows reducing forecasting error from 6-5% to 2-1.5%, as the test results showed.

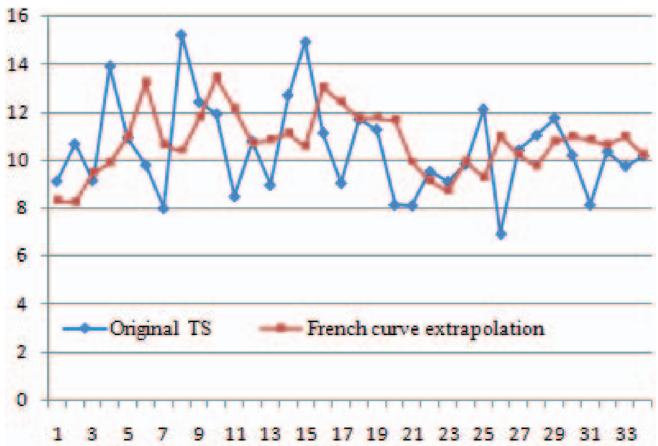

Fig. 2. French curve extrapolation. The RMSE of the time series without model regularization.

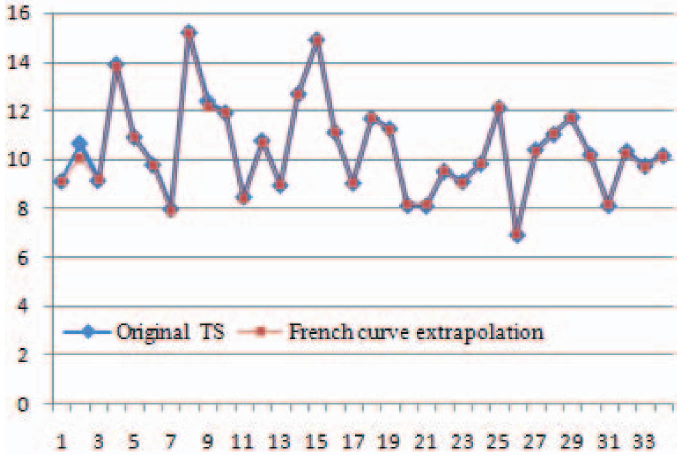

Fig. 3. French curve extrapolation. The RMSE of the time series with model regularization.

IV. Ontology Model

An ontology module preserves and shares context knowledge on behalf of the energy consumption, restricted by resources, and a computing entity. We propose a context ontology model for efficient knowledge sharing, knowledge reuse, context querying and reasoning.

An ontology (describing the information space of CAEMS) includes a description of the following classes: Time, Location, User, Infrastructure, and Environment.

Integration into the context of the information received from heterogeneous sources allows obtaining the model of the real energy system present state. And the next step determines optimal control rules using this context.

Case-base reasoning with ontology can be seen as the core of the knowledge base, which can be populated with real data from different information sources (e.g., devices, sensors etc.) which can further be used as a basis for the creation of control rules [6, 9].

V. Context Prediction

Prediction of the context means the ability to predict the future context information in order to provide proactive service to the actions of all electrical facilities (loads and generators).

Based on the formal presentation of the context prediction task [10], we can formalize a prediction task as a follow:

$$Pr = G\ (S1, S2, \ldots, S_t). \quad (4)$$

St: the context data at a certain moment in time.
Pr: a prediction result.
G: operator of context prediction operation.

We address one of the most valuable context prediction tasks – learning human habits and behavioral patterns for indoor location prediction. The motivation behind choosing this problem is that knowledge of the location, presumably entered by the user, can initiate several preparation routines to maximize comfort and minimize energy consumption. Automatic adjustment of light or temperature, by heating rooms prior to their occupation, can be stated as an example of such a routine.

The classic definition of location prediction considers a set of locations visited for a fixed amount of time steps. The data for location prediction usually has the form: <time, Object, Location>. Given a number of previous visits, the goal of location prediction is to find the most likely location for the next timestamp. Location prediction limits the locations to rooms or offices inside a building.

We evaluate several popular and well-established location prediction techniques: (Naive Bayes [11], Decision Trees, Support Vector Machines [12]), as well as some algorithms which achieved high accuracies on different supervised learning tasks (Random Forests [13], Ensemble of several models). Accuracy for 4 precious locations setting is shown in Table 2.

TABLE II. ACCURACY FOR PRECIOUS LOCATIONS SETTING (LS) OF 1 AND 4

No.	Algorithm	Accuracy		No.	Algorithm	Accuracy	
		1LS	4LS			1LS	4LS
1	Decision Trees	0.72	0.78	*4*	Naive Bayes	0.50	0.74
2	Random Forests	0.72	0.80	*5*	Voting	0.72	0.79
3	Support Vector Machines	0.73	0.78	*6*	Gradient Boosting	0.73	0.80

The results show that the introduction of additional previous location improves the accuracy of almost every model. Highest accuracy in a column is shown in bold. The Support Vector Machines and Random Forests outperform every other model. The Support Vector Machines and Random Forests standalone can achieve high scores, but their combination via voting proves to be powerful enough to be implemented in practice.

VI. CONCLUSIONS

In this paper, the CAEMS framework capable of context reasoning is presented. It involves the following steps:

Step1: Sensor data acquisition and Feature extraction.

The proposed approach of regularization of time series for forecasting method allows reducing forecasting error from 6-5% to 2-1.5%.

Step2: Ontology model.

Integration Case-Base reasoning technology and ontology approach in CAEMS allow to hidden interdependence between classes of ontology which describes the operation of the converter in a unified information space and used only necessary and allowable information and knowledge.

Step 3: Context prediction.

We have evaluated several models location prediction. Although the resulting prediction accuracy is below 80%, Support Vector Machines and Random Forests prove to be the most appropriate models for location prediction in a classic setting which involves only the history of visited locations. Such algorithms can be successfully implemented as a part of a context-aware energy management system.

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