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CONTEXT DATA ANALYSIS FOR MICROGRID CONTROL SYSTEM

За останні кілька десятиліть попит на електроенергію зростає, тому в останні роки, швидко розвиваються системи керування в області мікрогрід, що включають в себе керування як поновлювальними джерелами енергії так електричними навантаженнями. Системи керування у мікрогрід повинні мати змогу опрацьовувати великі обсяги даних, що пов'язані як з енергетикою, так і бути у змозі реагувати на зовнішні зміни контекстних даних. У статті описується модуль аналізу контекстних даних, що входить до системи керування мікрогрід.

Over the past few decades the energy demand has been continuously increasing (both in industrialized and in emerging countries) and the control systems for renewable sources and electrical loads have become much more sophisticated. Through the last years we have seen increased interest in the area of Microgrid control system. Today they are highly distributed, can manage large amounts of energy related data and have to be able to react rapidly (but smartly) when conditions change. The paper describes these challenges and presents data management solutions as a module of context data analysis for Microgrid control system. These solutions include time series forecasting, managing subscriptions for prediction energy supply and demand and analytical query processing past and future context data.

1. Introduction

A microgrid comprises medium- and/or low-voltage distribution systems with distributed energy sources, storage devices and controllable loads. They can operate either if connected to the main power network or if isolated (islanded) in a controlled and coordinated way. Frequently we refer to a self-sufficient interconnection of distributed generation, residential and industrial load in a low-voltage network without a persistent connection to a larger grid [1, 2].

The main goal of the microgrid concept is to create a control system that will be able to prediction and react smartly to the actions of all electrical facilities (loads and generators) connected to it, by means of converters in the unified information environment. The system should be able to rationally utilize energy, efficiently control normal and emergency conditions and to take into account the user comfort. Microgrid control system as a complex information processing system integrates such organization levels as: Renewable sources of energy; Electrical devices; Digital sensors; User tasks [3].

Microgrid is tightly interconnected with sensor networking, allowing behavior prediction and fault detection. There must be a constant balance between user comfort and energy efficiency. Viewed as an energy system, i.e., one with energy input/output and internal energy flows, a microgrid control system presents an example of a deeply coupled system of energy usage, comfort and performed work. Currently, efforts are aimed at the improvement of energy efficiency to decrease energy costs [4].

The paper focuses on the development of the module of context data analysis for Microgrid control system, which is designed to minimize user's costs and ensure the most comfortable conditions in microgrid. It is engineered with the use of a new method which consists of context prediction obtained from sensors of Microgrid.

2. Model of context

Load and generators management in microgrid is connected with the difficulty of analyzing the current situation due to its continuous alteration and the necessity for additional information-processing equipment to process the huge amount of heterogeneous sources [5]. One of the artificial intelligence (AI) tools introducing handy and understandable model representation is the context model.

Context can been defined as any information that can be used to characterize the situation of an entity, where the entity is a person, place, or object that is considered relevant to the interaction between a user and an microgrid control system, including the user and application themselves [6, 7].

Integration into the context of the information received from heterogeneous sources allows obtaining the model of the real microgrid present state (Fig. 1).

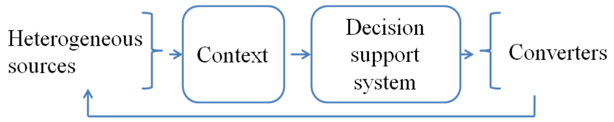

Fig. 1. Context conversion structure.

Context is formed as a result of an event generated by microgrid sensor data. Conversion of the measured data to context is shown in Table 1.

Table 1. Conversion of the Measured Data to Context

Context source (from sensors)	Raw data	Context
thermometer	00100111	14 °C
microcontroller (current sensor)	00110010	2 A

Context attributes of microgrid:
- Physical (Lighting, temperature, acceleration etc.);
- Computing entity (connectivity, network bandwidth, network latency etc.);
- Equipment (loads, energy sours, sensors etc.);
- Time of synchronization (time of day, weekday, month, season of year etc.);
- Action at previous action time (get, set, subscribe, unsubscribe);
- Architecture (zone or location).

Context prediction requires the consideration of the time dimension. A set of observations $t_1 \ldots t_n$ with t_l being recorded at a specific time interval t_i is called a time series [9]. A discrete time series is one in which the observations t_l are taken at discrete time intervals. Despite a sample quantity of publications about time series processing methods, the problem of practical application of these methods under the conditions of dynamic operational conditions of the converters is actual.

3. An approach to context parameter prediction

Predictions require the specification of a stochastic model that captures the dependency of future or past values. We will refer to such models as the prediction models. Usually the creation of the prediction models is computationally expensive and often involves numerical optimization schemes to estimate model parameters. Once the model has been created and the parameters estimated, it can efficiently be used over and over again to predict future values of the time series. As the new data arrives, the prediction model might require maintenance in form of parameter re-estimation. This is computationally expensive while most parameters cannot maintain constant step-size [10].

The following algorithm is provided for module of context data analysis. It's peculiarity lies in an improved performance and additional functionality inside the input parameters of the time series database.

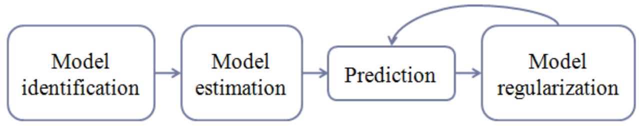

Fig. 2. Formalized procedural path of the prediction process.

Model Identification.

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 [11, 12]. Keeping 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 obtain trends [13, 14]. Thus, the first step of the module of context data analysis is the filtration and the second step is the prediction.

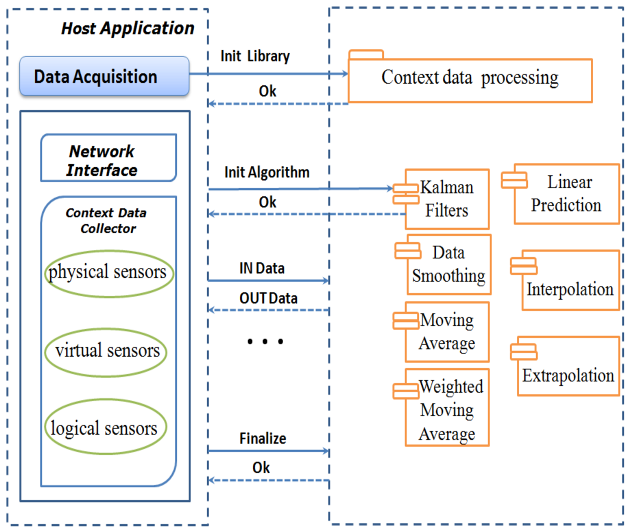

Fig. 3. Raw sensor context data analysis.

There are three distinct groups of smoothing:
- Averaging Methods – moving average, weighted moving average;

- Exponential Smoothing Methods – simple, weighted, exponential, double;
- Kalman filter.
- And three group of prediction:
- Interpolation – linear, polynomial, spline;
- Extrapolation – linear, polynomial, French curve, conic;
- Linear prediction.

Model Estimation.

The Table 2 consist of the lists initial parameters for prediction algorithms.

Table 2. Parameters for Prediction 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 (Fig.4).

1) Assign γ, n and n values;

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

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

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

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 timestamp $X(t_k+\gamma)$. If there is such an element, where Q(tk+γ) is a root-mean-square error (RMSE) of a time series values being predicted from the real $X(t_k+\gamma)$ as in (2)

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

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 tk, the algorithm goes to step 2).

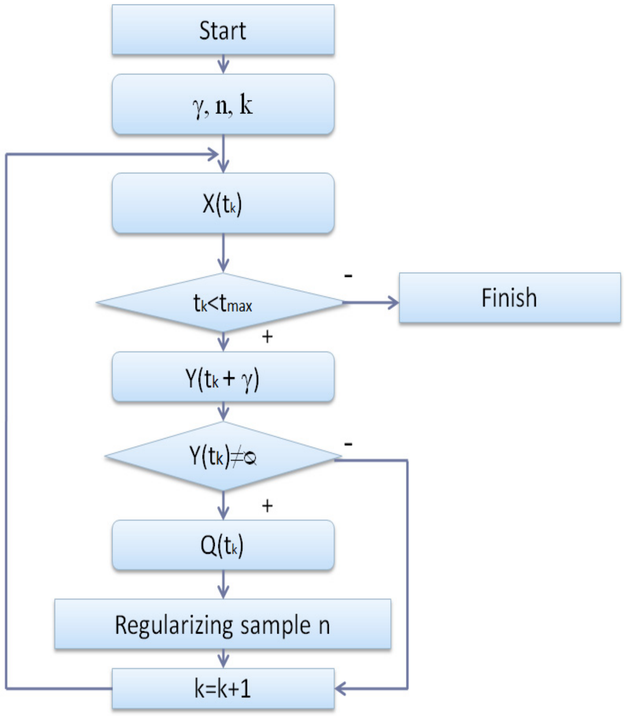

Fig. 4. General prediction algorithm.

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}.

Model Regularization.

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 (Fig.5).

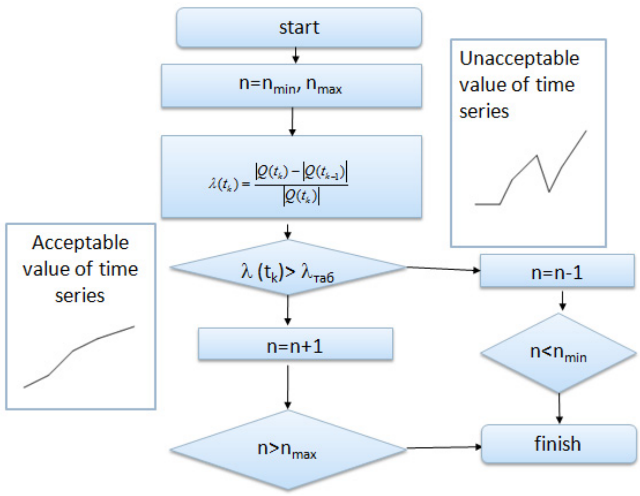

Fig. 5. Regularization algorithm.

1) Assign n= n_{min} , n_{max}=max;

2) Read the RMSE $Q(t_k+\gamma)$ from 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):

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

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

This prediction approach with 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 Microgrid.

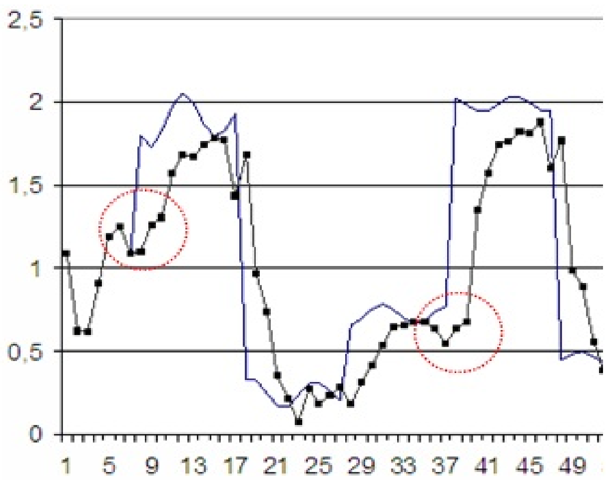

Fig. 6. a) Linear prediction. The RMSE of the time series without model regularization.

Figure 6 (b) 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.

After module of context data analysis, control algorithms can generate a variety of control decisions coming on the microgrid converter assembly. Therefore, microgrid control system is a smart decision support system, which adjusts to the context alteration by means of its operation algorithm alteration.

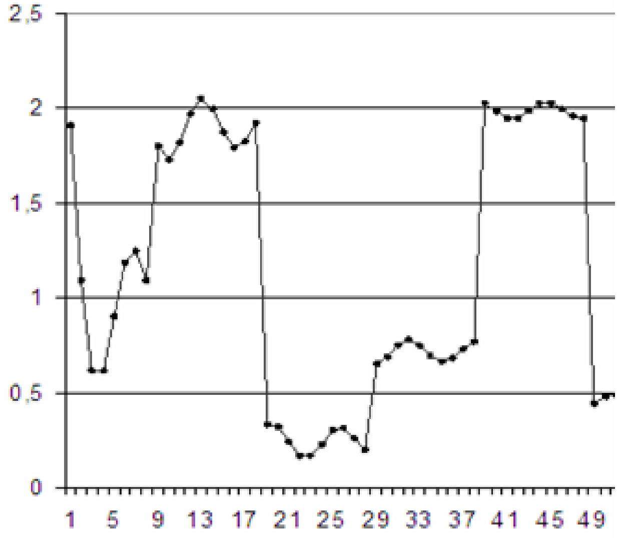

Fig. 6. b) Linear prediction. The RMSE of the time series with model regularization.

4. Conclusion

The integration of prediction inside a Microgrid control system is a rising topic in the research community. We have described the module of context data analysis for Microgrid control system that facilitates a more efficient utilization of renewable energy sources by taking benefits of energy flexibilities.

The proposed module regularization (adaptation) of time series for prediction method allows reducing forecasting error from 6-5% to 2-1.5%, as the test results showed. Program application approach of regularization its initial version so that there is still the room for improvement. Firstly, the current approach can be extended to support other forecasting methods (e.g., ARMA, ARIMA). Secondly, it can increase the accuracy of future data forecasts. Finally, we obtain faster approximate results of historical data and increased performance of data loading.

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