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IoT-based Energy Management Assistant Architecture Design

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Abstract— The Internet of Things (IoT) provides opportunities to control interconnected smart devices via pre-designed scenarios with little or no human involvement. Due to the need for systematic improvement of industrial energy efficiency, the relevance of IoT-based energy management systems (EMS) is constantly increasing. Industrial IoT (IIoT)-enhanced EMS are created to support the digital transformation of enterprises. They increase the transparency of energy consumption statistics, enhance the personnel awareness of energy losses, provide predictive analytics tools for forecasting potential industrial accidents and future energy demand. This paper hence provides a system architecture of the energy management assistant that can be used at enterprises to archive the aforementioned aims.

Authors identify the relevance of EMS, list the conditions at modern enterprises that define the requirements for the energy management assistant, demonstrate the identified requirements in the UML diagrams. Specification of energy planning and energy monitoring stages demonstrate the possibilities of the designed system architecture. For demonstration purposes, authors present examples of linear and nonlinear regression models implemented to specify energy consumption target functions based on real data. Finally, future research directions and open energy management problems are presented.

The analysis has been carried out within the priority area of scientific development established in the National Research University Higher School of Economics – "Research on control methods in Cyber-Physical Systems".

Keywords— internet of things, energy management system, energy efficiency, architecture design, digital transformation.

I. INTRODUCTION

The increasing of operational quality while reducing energy expenses at the enterprise, e.g. arising from purchasing of energy sources and energy consumption, is one of the priorities within the digital transformation concept. Energy consumption optimization can be realized via the implementation of energy management principles. They are aimed at managing enterprise energy flows and using efficient ways of energy consumption in accordance with the company goals. Energy management, as a subsystem of the quality management system, contributes to the achievement of the strategic goals and increases enterprise competitiveness. Energy balances analysis conducted by Russian Federal State Statistics Service had shown industrial production to be the most energy-intensive activity in Russia as it is consuming more than 50% of the total amount of distributed energy resources. Energy management systems (EMS) implementation at enterprises enables energy consumption optimization, energy data analysis and quick decision-making regarding energy management. They provide opportunities to qualitatively improve the production cycle characteristics, efficiently manage industrial energy costs, timely undertake energy-saving measures, predict the future energy demand [1].

The Internet of Things (IoT) technologies [2] [3] [4] facilitate achieving energy efficiency. The IoT is a paradigm of wireless telecommunications that enables:

- incorporation of heterogeneous objects such as sensors, actuators, electronic devices, etc.,
- interconnection of heterogeneous objects,
- collection of enormous amounts of data produced by such objects,
- provision of new services based on the data collected [5].

The IoT technologies find application in various domains: home and industrial automation, healthcare, management of public services such as parking [6], lighting, garbage utilization, traffic congestion tracking, public areas maintenance, thus realizing the Smart City concept [7].

The IoT is applied in smart energy management to provide increased economic efficiency and competitiveness as well as improved productivity of enterprises. These benefits are gained due to:

- increasing transparency of energy consumption statistics [8] and its accessibility improving [9],
- enhancing the awareness of energy managers about the amount of energy required to maintain enterprise functionality,
- identifying the major energy consumption sources and energy losses in real time,
- providing predictive analytics tools for forecasting potential industrial accidents and future energy demand.

Therefore, IoT-based EMS, as an energy management tool for an enterprise, is a significant component of the Smart City concept and is particularly beneficial for enterprises interested in energy consumption optimization,

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e.g. producing more output maintaining the same level of energy input.

The need for customizable realization of EMS appears due to commercial distribution of software available on the market and hidden architecture features of the energy management solutions that makes it difficult to adapt the analytical components of the systems to specific enterprises and operating conditions [10]. Moreover, the cost of available energy management platforms is quite high, they are characterized by increased requirements not only to the personnel qualification but also to the operating conditions. This impedes the creation of efficient industrial enterprises [10]. Thus, open EMS architecture design is a perspective direction of economic development in the conditions currently prevailing on the market.

A thorough analysis of the ISO 50001: 2011 standard has been carried out, and all suggestions regarding the energy management cycle stages have been taken into consideration while modelling the architecture of the proposed assistant. However, it has been revealed that the standard's consultative nature and lack of specific energy management measures to be taken complicate the energy management digitalization. Thus, the contribution of the research is the digitalization of energy management assistance via the specification of the ISO 50001: 2011 standard requirements and integrating IoT-based technologies into EMS. The research objective is to provide a generic IoT-enhanced architecture of the energy management assistant that can be used to facilitate energy management at enterprises.

The research design adopted in this study involved, firstly, literature review of energy management principles and implementation of IoT practices. Secondly, review and consolidation of theoretical knowledge and practical experience gained as a result of EMS deployment at real enterprises were used to collect the requirements for the IoT-enhanced assistant. Assistant's architecture was designed in the UML notation. Finally, the models were evaluated by the experts in the field of energy management and IoT.

The paper is organized as follows: Section II represents our findings on IoT platforms and energy management practices. In Section III we define requirements for the energy management assistant derived from the analysis of the conditions at modern enterprises, demonstrate them partially in the UML diagrams. Energy planning and energy monitoring stages of the energy management cycle are described in more detail in Section IV. The proposed energy management assistant architecture designed based on the identified requirements is introduced in Section V. Section VI presents examples of loss functions calculation based on real enterprise data. Finally, conclusions and future work are proposed in Section VII.

II. Related work

In this section, we describe our findings obtained from the literature review in the field of EMS, IoT technologies and attempts to implement IoT to the energy optimization processes.

At the majority of Russian enterprises and city facilities, energy management is carried out inconsistently. A methodology has been proposed to measure the state of energy management at an enterprise [11]. According to the results of its implementation and the revealed state of energy management, particular recommendations can be given for the development of EMS at an enterprise. It is also noted that for the majority of large Russian enterprises the results of energy management state tests are not high. The energy saving measures at the majority of enterprises are limited to the use of new materials and equipment, analysis of opportunities to improve energy efficiency is carried out only for selected processes.

The majority of EMS systems deployed at enterprises build dependencies between the amount of resources consumed, the factors influenced the consumption and the costs. Energy saving recommendations are mostly based on common practices or the experience of external specialists, most often only data from energy meters are taken into account, elements for automatic or automated control are only available in expensive solutions provided by Siemens, ABB, Schneider Electric and others.

In order to identify how IoT-based technologies can facilitate energy management, it is necessary to review the achievements of IoT implementation in different subject areas. For example, in [7] authors provide a comprehensive survey of Smart City services that can be realized with the help of IoT technologies, present a general urban IoT architecture that integrates various peripheral devices, enables data transmission, storage and processing. The introduced practical implementation of an urban IoT is aimed at collecting environmental parameters and monitoring the operation of the public lighting system, however, the architecture excludes any analytical components that would realize energy management principles in the aforementioned lighting system. The micro-environment parameter monitoring system presented in [12] is characterised by the same lack of analytical components. However, it describes in detail the principles of sensor network functionality.

A comprehensive study is introduced in [6] whose authors propose a smart-parking system (SPS) based on IoT technologies that not only monitors and manages car parks but also minimizes the drivers' costs of moving to the parking space. The architecture and the mathematical model of the cloud-based system are presented and the high performance of the SPS is approved via simulation and implementation, thus demonstrating the IoT concept application in solving the problem of costs reduction. However, the research is aimed at the minimization of time and money users spend waiting for the service while the question of energy consumption is not considered, thus leaving great scope for future work concerning IoT implementation in EMS.

The question of the energy efficiency of the IoT itself is considered in [13]. The principles of green information and communications technologies (ICTs) are described by the authors, some of them are: turning off facilities when not in use (e.g. sleep scheduling), minimizing the data path length, combining data collection from multiple resources. Authors also overview the sensor-cloud technologies aimed at reducing the energy consumption of IoT.

Some of the challenges regarding energy management that were observed in related works are listed hereafter. In [14] the implementation of IoT technologies is aimed at achieving energy efficiency of a smart household and two problems are considered by the authors - load scheduling of smart home appliances and dispatching of energy drawn from the utility grid. Another challenge arising in the process of energy monitoring is detecting and processing abnormal data that otherwise can affect statistical patterns and analysis results. Questions regarding dealing with the outliers are considered in [9] whose authors propose a methodology based on the first order difference model that can be implemented in building energy monitoring platforms for finding and processing the abnormal data. One more common difficulty is that the buildings' energy performance in most cases does not meet the projections made at the building design stage. The reasons for that are the use of unrealistic input data for the predictions and the lack of feedback on the actual energy consumption to designers [15]. The predictive energy modelling in addition to the energy monitoring is proposed to reduce the gap between the expected energy consumption levels and the in-use performance of buildings [15].

General IoT system architecture for energy management is demonstrated in [16]. Authors derived the architecture that depicts the layer of sensors and smart meters connected to different monitoring targets (production lines, machines, etc.), the getaway responsible for the data transferring to local computers and to the internet, and the layer of enterprise resource planning systems. The local and cloud servers responsible for the energy data storage and analysis are shown. However, the architecture is aimed at energy monitoring only, other stages of the energy management cycle are being ignored that significantly limits the potential advantages derived from its implementation. Moreover, the architecture lacks the specification of analytical services at the server level. Thus, the outcomes of our research compare favourably from the mentioned above architecture and benefit from the specification of services that realize the full energy management cycle.

The aforementioned findings and observations made while studying the current state of energy management processes at modern enterprises enabled us to complete the requirements to the energy management assistant tool that are presented in the next Section.

III. Energy Management Assistant Requirements

EMS design for an industrial enterprise should be initiated by the identifying of target business processes. For that purpose, an abstract industrial enterprise characterised by significant energy consumption is taken into consideration. Standard processes typical for industrial production are described hereafter in order to design general EMS architecture that can be adapted to any specific subject area and operating conditions.

Hereinafter we define industry as a system of various sectors engaged in the extraction of raw materials and processing them into goods. Industrial enterprises are characterized by production and technological, organizational and financial unity, economic independence whose main purpose is to provide society with required goods. The production of such goods is followed by enterprise energy consumption costs. The total costs consist of the energy sources purchasing, which is complicated by the selection of energy suppliers, appropriate energy tariffs, and energy consumption. Unwarranted expenses occur due to energy losses caused by leaks, measurement and manual input errors, equipment downtime, malfunction of measuring tools, inaccurate cost accounting, etc. Energy management assistant should be able to avoid any unexpected or unwarranted costs.

Successful EMS system realization, implementation and operation requires taking into account such factors as the number of people in the room, the number of working equipment, environmental parameters, season, etc. This is achieved through the implementation of special IoT sensors [17][18] that collect data in which hidden patterns can be detected and controllers that propose solutions, e.g., automatically turn on / off lighting, control the heater valve, adjust the climate parameters via the air conditioner, control the equipment according to pre-designed scenarios, forecast failures and accidents [17][18].

According to the ISO 50001: 2011 standard that describes requirements to EMS systems, energy management is realized within the Shewhart-Deming cycle - PDCA (Plan, Do, Check, Act). This cycle demonstrates the concept of continuous improvement, and specific actions are assigned to each stage of the cycle. Thus, the "Plan" phase is mainly energy planning - energy policy creation, energy demand identifying and energy expenses calculation, energy-saving measures planning; "Do" - energy saving measures implementation, e.g. equipment parameters setting; "Check" - energy efficiency examination: equipment operation analysis, accident and losses analysis, plan-fact analysis; "Act" - corrective actions - discrepancies assessment, energy policy updates. Energy management assistant architecture should be designed in consideration with the requirements of this standard.

The main advantages of the standard are its inclusion in the national energy efficiency programs within the digital economy concept and the applicability of applying to all industries [19]. Despite the advantages, the drawback of the standard is a too generalized description of the EMS systems creation and implementation [20]. Thus, the contribution of the research is the digitalization of energy management assistance via the detailing of the standard requirements, specifying energy management stages and using IoT-based technologies.

The requirements to the energy management assistant were introduced in the UML use case diagram. It is partially presented in Fig. 1 and Fig. 2. Fig. 1 depicts the specification of energy planning in which energy manager, chief power engineer and top manager take part. In Fig. 2 energy efficiency monitoring specification is shown. Energy manager and enterprise personnel are involved in energy efficiency monitoring.

The obtained models were demonstrated to the industry professionals - experts in business-informatics and software engineering, integrators of building management systems and Smart Home systems, and experts in IoT technology. Relying on their evaluation the relevance of the proposed models was confirmed.

The identified requirements were used for the IoT-based energy management system architecture design that is introduced in the next Section.

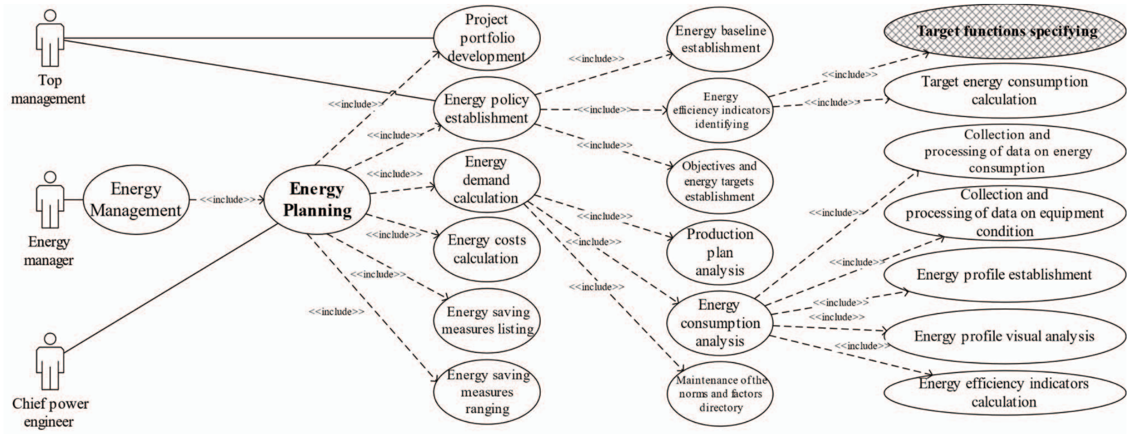

Fig. 1. Energy planning stage of the EMS PDCA cycle

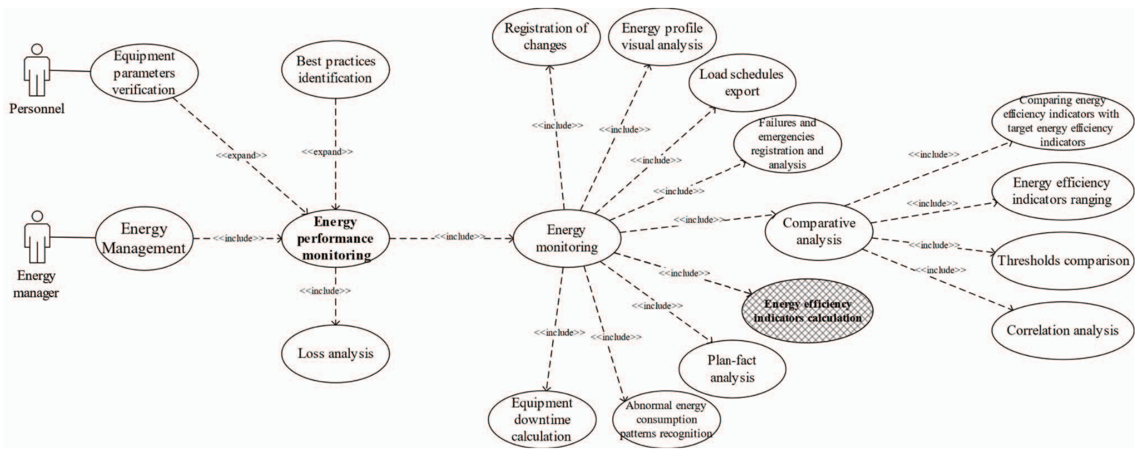

Fig. 2. Energy monitoring stage of the EMS PDCA cycle

IV. Energy planning and energy performance monitoring models

In this section, particular precedents of *energy planning* and *energy efficiency monitoring stages* are described in detail. Thus, at the *energy planning stage,* the process of target function specification (Fig. 1) is considered (section A). At the *energy performance monitoring stage,* special attention is drawn to the process of energy performance indicators calculation (Fig. 2, section B). These processes should be automated by the energy management assistant.

A. Model for target functions calculation

The sequence diagram was created to identify the steps of the target functions calculation with the help of regression analysis since this use case is considered to be one of the most significant at the energy planning stage. (Fig. 3).

The diagram illustrates the sequence of user actions aimed at collecting data and performing the regression analysis. Examples of relationships among variables that can be estimated via the regression analysis are introduced in Section 6, however, it is significant to specify the process of calculation first.

The abbreviations in the diagram (Fig. 3) stand for: E – energy manager (actor), EA – energy manager account, RAF – regression analysis form, N – notification, CPEA SEA – chief power engineer account, CPE - chief power engineer (actor), DBC – database controller, SCC – statistics calculation controller, EC – Energy Consumption, DB – Database, MLS – the least squares method, TSst – Test of significance (Student), Corr – correlation coefficient, FC – Fisher criterion.

The process of target function calculation (regression analysis) is aimed at understanding how the typical value of the dependent variable (or ‘criterion variable’) changes when any one of the independent variables (or ‘predictors’, ‘regressors’) is varied, while the other independent variables are held fixed. Thus, regression analysis is started by the energy manager who defines possible predictors and sends a request to the chief power engineer in order to get a confirmation of the chosen independent variables. Next, the necessary for the analysis data is partially uploaded from the

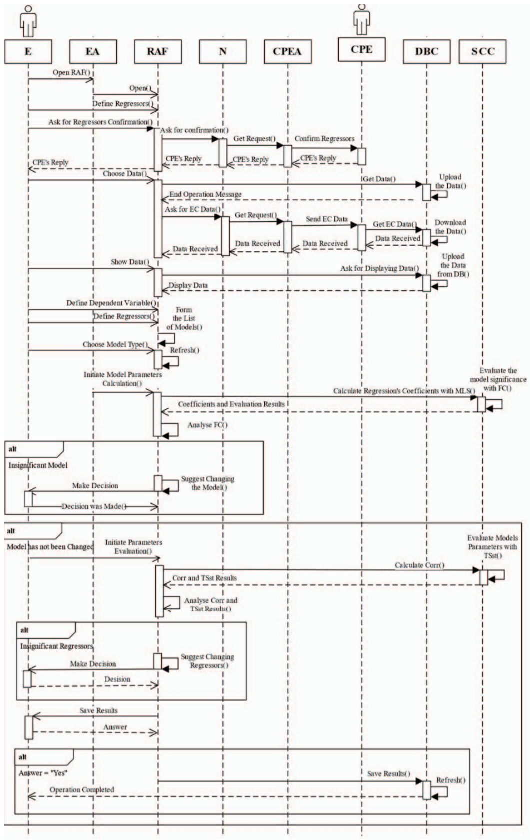

Fig. 3. Sequence diagram “Target functions specification”

database whereas the rest of the data can only be provided by the chief power engineer. When all data is received, the energy manager specifies what time series describe the dependent variable and what time series refer to independent variables and selects the type of the regression model. The energy manager assistant then calculates the regression coefficients with the least squares method, evaluates the model significance. In case of good results, the analysis is continued with model parameters evaluation (evaluation of the regression coefficients), the implementation of the Student test of significance evaluation and checking the correlation coefficient between model parameters. The conclusion of whether the regressors where chosen right or not can be made by the energy management assistant based on the information retrieved. The process of saving the results is also shown in the diagram.

The created sequence diagram helps to identify methods that will be performed by the corresponding classes in the system and actors that will initiate the execution of these functions.

B. *Energy efficiency indicators calculation*

Target functions should be specified by metrics named EEI - energy efficiency indicators. Calculation of the EEI by the energy management assistant is considered in this subsection.

The EEI key set is formed via metering data, equipment parameters and their combination within the energy efficiency management cycle. For industrial enterprises the main EEI is the energy capacity of the products - the value of the specific energy consumption per production unit. It determines the amount of energy consumed per production unit at the enterprise. The EEI can take various modifications depending on the type of energy source for which the calculation is provided. Various modifications are introduced in Table I.

Every industrial equipment unit (IEU) can be described as the following aggregate:

$$IEU \overset{\text{def}}{=} \langle Id, St, Fn \rangle,$$

where *Id* is the identificator of an industrial unit, *St* – the set of initial state EEI, *Fn* – the set of target functions.

TABLE I. KEY ENERGY PERFORMANCE INDICATORS

№	*Parameter name*	*Formula*	*Comment*
1	Specific fuel consumption index for heat boilers, kg.t/Gcal	$b^{fact} = \frac{B^{fact}}{Q^{prod}}$	B^{fact} – the actual fuel consumption, kg.t. Q^{prod} – the total amount of thermal energy produced per year, Gcal
2	Specific electricity consumption index	$w^{fact} = \frac{W^{fact}}{Q^{prod}}$	W^{fact} – actual electricity consumption, kg.t. (kWh)
3	Heat consumption index for boilers’ own needs (%)	$K_{s.n.} = \frac{Q_{s.n.}}{Q^{prod}}$	$Q_{s.n.}$ – actual thermal energy consumption, kg.t. (Gcal)
4	Energy efficiency indicator for thermal energy heating at enterprises	$q_{jil} = \frac{Q_{enter}}{F_{centr}}$	Q_{enter} – the actual amount of thermal energy used by the enterprise, Gcal; F_{centr} – total enterprise facilities area with central heating, m^2
5	Specific thermal energy consumption for the heating of enterprise facilities equipped with metering devices	$q_{equipped\ facilities} = \frac{Q^{fact}}{F_{equipped\ facilities}}$	Q^{fact} – the actual amount of thermal energy read from an external network by metering IoT devices; $F_{equipped\ facilities}$ – total enterprise facilities area equipped with metering devices, m^2
6	Percentage of buildings equipped with metering devices for thermal energy	$K_{equipped\ buildings} = \frac{N_{centr}}{N_{facilities.centr}}$	$N_{facilities.centr}$ – the number of buildings with central heating, units; N_{centr} – the number of buildings with central heating equipped with metering devices, units.
7	Metering devices usage index for thermal energy	$K_{metering\ devices\ usage} = \frac{N_{met.dev.therm.en.}}{N_{met.dev.}}$	$N_{met.dev.}$ – total number of installed metering devices, units; $N_{met.dev.therm.en.}$ – the number of installed thermal energy metering devices, units.

Every EEI depends on different factors which can be energy-related, technical, technological and climate factors. Each aggregate is described by the set of the following factors:

$$St \stackrel{\text{def}}{=} \langle Cl, Thn, Thl, Pw \rangle,$$
$$Fn \stackrel{\text{def}}{=} \langle Thn, Thl, Pw, Op \rangle,$$

where Cl is the set of P indicators of the climate factor; Thn – technical factor; Thl – technological factor; Pw – energy-related factor; Op – operational factor:

$$Cl = \{P_{cl1}, P_{cl2}, \dots, P_{clm}\};$$
$$Thn = \{P_{Thn1}, P_{Thn2}, \dots, P_{Thnn}\};$$
$$Thl = \{P_{Thl1}, P_{Thl2}, \dots, P_{Thlg}\};$$
$$Pw = \{P_{pw1}, P_{pw2}, \dots, P_{pwj}\};$$
$$Op = \{P_{op1}, P_{op2}, \dots, P_{opq}\}.$$

Every P indicator is described as the set of values measured by IoT devices:

$$P = \langle name, \{value\} \rangle,$$

where name is the name of the indicator; {value} – value domain.

V. Energy management assistant architecture

The service-oriented architecture of the IoT-based energy management assistant is represented in the UML component diagram (Fig. 4).

The client level is presented by equipment that collects data on energy consumption; web applications responsible for the users' interaction with the system are deployed on a web server [18]. At the application server level, such services as data collection, administration, documentation, optimization are deployed, as well as four energy management services responsible for the PDCA cycle. Message broker is used to exchange information between the services and save necessary information at the database server.

The energy planning service is designed to maintain energy analysis: it performs energy sources evaluation, energy profile establishment, energy-consuming equipment efficiency identifying, base level energy consumption calculation and energy efficiency indicators identifying in order to compare the amount of consumed energy in different time periods, setting goals and objectives.

Energy-saving measures service is responsible for setting up the equipment parameters in accordance with the energy profile. The energy efficiency monitoring service performs monitoring [21]-[23], equipment functioning analysis, calculates the percentage of energy savings gained by energy saving measures undertaken at the current iteration. The block of corrective actions is designed to perform the discrepancies assessment.

Thus, the anticipated outcomes from the designed energy management assistant implementation at the industrial enterprise include:

- a holistic approach for energy efficiency management,
- energy resources savings,
- labour intensity reduction,
- management decisions quality and speed improvement
- energy-saving measures efficiency improvement due to the best practices accounting and implementation,
- increased information reliability,
- the attraction of investments.

VI. The implementation of linear and nonlinear regression models to specifying energy consumption target functions

In practice, EEI are calculated based on the time series analysis. Time series are generated by IoT devices that monitor energy consumption parameters and process characteristics. IoT devices have an interface for connecting to the Internet or to the enterprise local network and can be easily connected to the Internet of Things platforms. The energy manager's interface view in the energy monitoring mode in ThingsBoard IoT platform may look like the one shown in Fig. 5-6.

Examples of target functions that should be specified by the energy management assistant are introduced hereafter and could be realized via ThingsBoard Rule Chain tool. The dataset for the regression analysis is presented in Table II and reflects the number of product output, the amount of heat generated, and gas consumed by an enterprise and the ambient temperature per month throughout a year. Fluctuations of the input data points strongly depend on the energy consumption efficiency of the enterprise. Input data

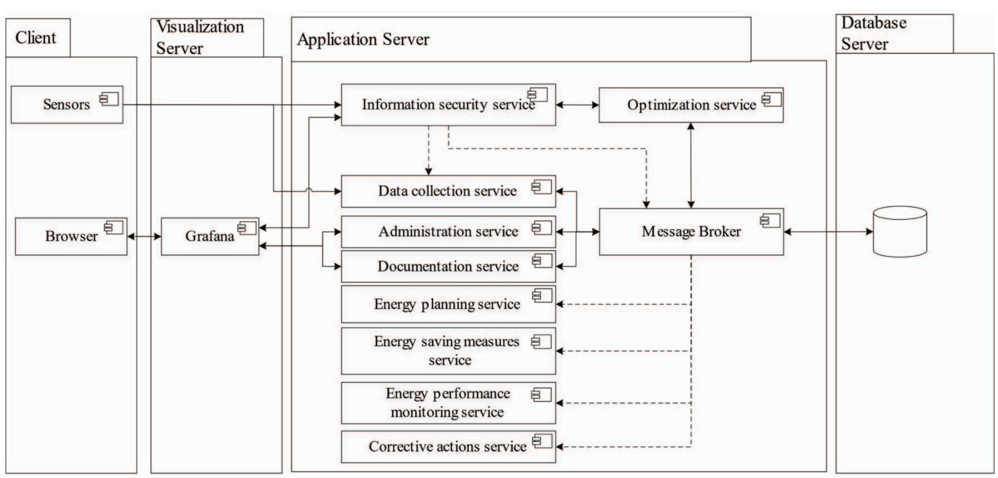

Fig. 4. The generic IoT-based energy management assistant architecture

Fig. 5. Energy manager's interface in energy monitoring mode

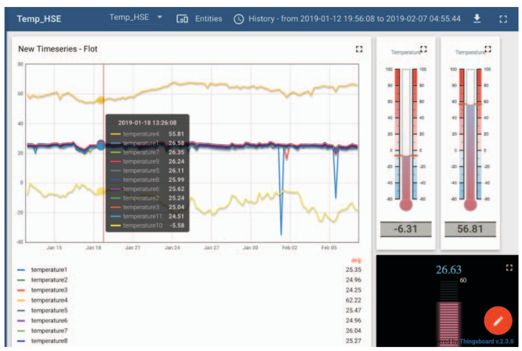

Fig. 6. Energy manager's interface in energy monitoring mode

was collected prior to the implementation of any energy consumption optimization measures. However, once energy management is properly organized the input data points should approach to a linear model.

The objective of the regression analysis is to identify whether there is a relationship between the dependent and independent variables. The specification of the models that demonstrate the relationship, i.e. the determining of the coefficients for independent variables and the intercept, was carried out according to the algorithm presented in the Sequence diagram (Fig. 3).

The dataset allows identifying the following kinds of relationships:

- the dependence of gas consumption on the ambient temperature,
- the dependence of heat generation on gas consumption,
- the dependence of output volume on the heat generation,
- the dependence of heat generation on the ambient temperature.

For each of the relation type six regression models were specified:

- Linear: $P(t) = b_1 t + b_0$;
- Polynomial -2: $P(t) = b_2 t^2 + b_1 t + b_0$;
- Polynomial -3: $P(t) = b_3 t^3 + b_2 t^2 + b_1 t + b_0$;
- Hyperbolic: $P(t) = \frac{b_1}{t} + b_0$;
- Exponential-0: $P(t) = t^{b_1} \times b_0$;
- Exponential-1: $P(t) = e^{{b_1}^t + b_0}$;

A. *The dependence of gas consumption on the ambient temperature*

The relationship between gas consumption and the ambient temperature is shown in Fig. 7. Parameters of each of the six regression models are presented in Table III. For this relationship, the linear model is preferable since other types of functions are significantly distorted at intervals without data.

B. *The dependence of heat generation on gas consumption*

The results of regression analysis for heat generation and gas consumption are presented in Fig. 8 while the coefficients and the intercept of each model are specified in Table IV. The linear model is preferable for this relationship as other functions are significantly distorted at intervals without data.

TABLE II. INPUT DATA FOR REGRESSION ANALYSIS

Month	Output volume, tons	Heat energy, Gcal	Gas, м^3	Ambient temperature, C
Jan	17241.2	9 113.0	1118668	-13.1
Feb	21831.855	7 777.0	1098193	-14.5
March	22695.203	7 720.0	995428	-2
April	22824.582	7 153.0	886098	1.6
May	17596.471	5 924.0	736240	13.7
June	22231.671	5 167.0	672347	15
July	24752.536	6 795.0	712691	14.5
August	21106.082	6 457.0	656948	16.6
Sept	21194.933	5 783.0	732464	8.7
Oct	20472.163	7 770.0	924368	-1.3
Nov	20560.952	7 136.0	969414	-5.4
Dec	20587.361	8 134.0	1066482	-9.2

TABLE III. REGRESSION MODEL PARAMETERS FOR GAS CONSUMPTION/AMBIENT TEMPERATURE

R^2	Model type	b_0	b_1	b_2	b_3
0.973	linear	59.559	0.000		
0.973	polynomial -2	52.442	0.000	0.000	
0.973	polynomial -3	111.247	-0.0002	0.000	0.000
0.954	Hyperbolic	-53.799	47447983		
0.972	Exponential-0	70.100	-28.822	0.000	
0.970	Exponential-1	201.748	-4.152	0.283	

TABLE IV. REGRESSION MODEL PARAMETERS FOR HEAT GENERATION/GAS CONSUMPTION

R^2	Model type	b_0	b_1	b_2	b_3
0.791	linear	1983.348	0.005		
0.795	polynomial -2	4493.22	0.000	0.000	
0.795	polynomial -3	4014.68	0.001	0.000	0.000
0.000	Hyperbolic	7077.416	0.000		
0.795	Exponential-0	1392.223	2275.274	0.000	
0.784	Exponential-1	-19794.8	2172.11	0.183	

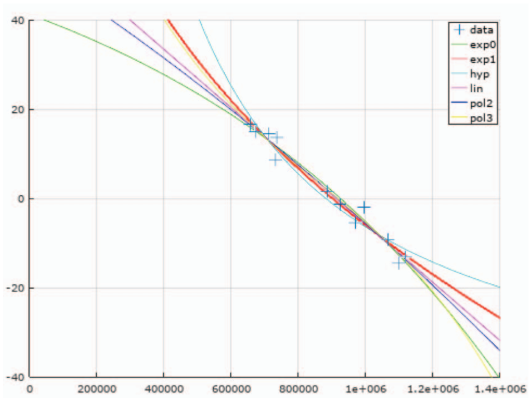

Fig. 7. The dependence of gas consumption on the ambient temperature

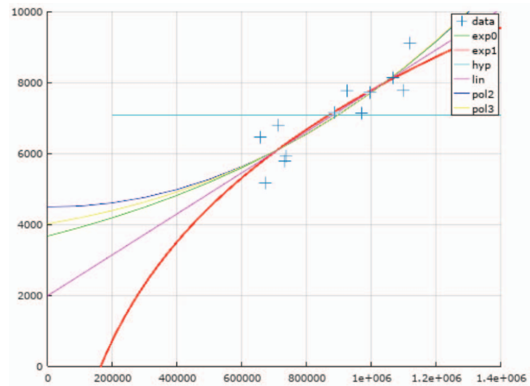

Fig. 8. The dependence of heat generation on gas consumption

VII. Conclusion

Due to the benefits gained via the implementation of IoT-enhanced energy management system, this energy management tool can be used within the digital transformation concept thus realizing the Smart City concept. Perspectives to increase economic efficiency as well as improve the productivity of enterprises makes IoT-based EMS promising and beneficial for enterprises interested in energy consumption optimization. Increasing transparency of energy consumption statistics, enhancing the awareness of energy managers, identifying the major energy consumption sources and energy losses, providing predictive analytics tools for forecasting future energy demand are highly demanded competitive advantages.

Findings on IoT platforms and energy management practices were represented in this paper. The requirements to the energy management assistant based on the conditions at modern enterprises were identified and presented in the UML diagrams. The proposed energy management assistant architecture designed based on the identified requirements illustrates how IoT technologies can be integrated into traditional EMS architecture. The service-oriented architecture style was chosen to represent the architecture of the IoT-based energy management assistant. All services of the client level, application server and database server were described.

The obtained models were evaluated by the experts in business-informatics and software engineering, integrators of building management systems and experts in IoT. Thus, the the relevance of the proposed architecture was approved.

The implementation of the designed energy management assistant provides enterprises with a holistic approach for energy efficiency management, leads to the energy resources savings, labour intensity reduction, the improvement of quality and speed of management decisions. The anticipated outcomes also include the increase in information reliability, the attraction of investments and identification of energy efficiency potential of an enterprise.

Finally, particular processes of energy planning and energy monitoring stages of the PDCA cycle were described in more detail in order to demonstrate some of the possibilities of the designed system architecture.

In the future study, the security aspects of the system as well as implementing the proposed system in large scales in the real work will be considered.

Acknowledgement

The analysis has been carried out within the priority area of scientific development established in the National Research University Higher School of Economics - "Research on control methods in Cyber-Physical Systems".

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