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Usage Of SaaS Software Delivery Model In Intelligent House Systems

***Abstract**. The article presents the usage of the SaaS cloud computing model in "intelligent house" systems for optimization of computation load between the client and server parts of the system. Also was developed artificial neural network model for detection of irrational electricity usage by devices of the "intellectual house".*

Streszczenie.** W artykule przedstawiono zastosowanie modelu przetwarzania w chmurze SaaS w systemach "inteligentnego domu" do optymalizacji obciążenia obliczeniowego między klientem a elementami serwerowymi systemu. Opracowano także model sztucznej sieci neuronowej, aby wykryć nieracjonalne zużycie energii elektrycznej przez urządzenia "inteligentnego domu". **Wykorzystanie przetwarzania w chmurze SaaS w systemach "inteligentnego domu"

Keywords: SaaS, intelligent house, artificial neural network, machine learning, control system structure.
Słowa kluczowe: automatyka domowa,.sieć neuronowa, uczenie maszynowe, struktura systemu kontroli

Introduction

In our days there are typical problems arise in process of smart houses development regardless of the type and system functionality [1, 2]. These problems arise at all steps of development, as on design process of the system and on the processes of integration and support [3, 4]. These common problems consist of system fixing, scaling, and functionality updates, the high cost of integration and support. The key role in avoidance of these problems plays the right choice of architectural implementation and information model of the intelligent building [5]. The usage of cloud computing SaaS (Software as a service) model creates the process of integration and support easier and cheaper. This solution is a complex combination of existing intelligent house control systems, where the main controller based on a microcomputer that controls all functions independently by itself and other systems that send sensor data parameters to the remote server and change intelligent house devices settings that are calculated on the server side according to current sensor parameters. Investigation of the scientific articles [6, 7, 8] give no results about scientific research of architecture optimization for the intelligent house systems that use artificial intelligence algorithms. It makes current theme very actual for reducing costs on intelligent house systems integration.

SaaS model basis

SaaS is the most popular model of cloud computing in the last years. The main idea of this model based on users access to ready to use software, that fully supported by the provider. The provider of this model supports the software by himself without user interactions, give the user access to the functions from client devices. The main benefit of the SaaS model for users is the absence of expenses for installation, upgrades, and support of the software. From the developer side, this service delivery model can effectively oppose to unlicensed use of software, because users do not get the code of the system but get only the endpoints of entry and exit functions in encapsulated and hidden implementation of these functions, performed on the side of the provider which provides current software. Also, this concept reduces the cost of deployment and integration of the systems and technical support.

SaaS functions in intelligent house development

Typically intelligent house functionality consists of house lighting devices management, including control of separate groups of lighting and control of separate devices, setting an appropriate level of lighting in separate parts of the house, turning on / off the light, depends on the location of people in the house; control of jalousies and curtains using electric motors, depending on the values of motion sensors in the house and sensor of outdoor lighting; control temperature in individual rooms of the house, depends on the preferences of the residents by usage of heating devices, ventilation, and air conditioning control; control of media devices in the house such as TV and sound system, depends on the people present in the house and their preferences. Also, intelligent house functions often include a security system that informs about entering the house of unrecognized person by usage of motion sensors in the building and surveillance cameras with face recognition software. Less common features of the intelligent house are damping land around the house based on indicators of soil moisture and seasons; management tub or pool heating and level of their fullness. In the intelligent house field, full transfer of the entire system functionality to the SaaS model is inappropriate due to the specificity of this area. Based on this complicated model building intelligent house system encounters difficulties with distribution and interaction modules responsible for specific well-defined functions that will be transferred for implementation in the cloud and that will be exec which execute locally on the client side. Separation of functionality on these two groups is important criteria for obtaining rapid response system. The functionality that requires a high-speed response and does not require big amounts of data should be done on the client side (collect data from sensors and fire protection functions, control devices at home). Functionality that requires processing large amounts of data using machine learning algorithms for automated decision-making and does not require high performance (regulate building temperature control) should be transferred to the technical side of the service provider.

Cloud computing of intelligent house functionality

Separation of functionality between the client part and provider gives benefits such as reducing the burden on the client side hardware of the system and gives the possibility for the provider to increase the database with real data. Reducing the load of the client side system hardware reduces equipment cost and the total cost of smart home installation for the end user. Basic functionality that does not require great technical capacity can be realized on the basis of popular microcomputers such as the Raspberry PI, Arduino, LattePanda and others that are characterized by small size and low cost. The main requirements for client software are the ability to collect parameters from all sensors that are located at home, the presence of the interface for connection to the Internet and the ability to manage devices using wireless home control technology. Big amounts of the real data can be used to improve the analysis and error elimination of the system and to optimize machine learning methods used for automated decision-making operations of the system [9, 10]. For intelligent house system such data are values of the optimal temperature in each room of the house, depends on the parameters of human presence in the house, season, time of the day, ambient temperature. Automated temperature and light management in intelligent house system allows to change thermostat and lighting settings [10, 11], based on the preferences of people without their direct involvement and helps to significantly reduce the financial costs of heating and lighting through optimization of resources usage in those parts of the building where they are needed, simultaneously maintaining these resources [12] in unnecessary parts of the house. This functionality is based on machine learning algorithms [13, 14] that require the initial training data, so the data transfer on the provider side can improve automated decision making results through training on real data [15].

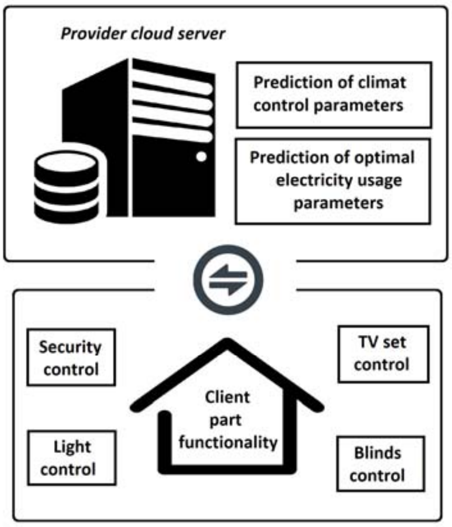

Fig.1. Scheme of local features and functions distribution in the cloud

SaaS model benefits

A key factor in the economical advantages of SaaS model usage is the scalability opportunity for the system based on this model. The provider maintains a software core that is single for all customers and as a result, needs fewer resources in comparison with separate software copies that is running for each user. In addition, the usage of a single software core allows streamlining the usage of the technical resources among users. This can reduce the cost of software maintaining, so the cost of the services for the end user of the system is lower than classical licensing model usage. The problem that has arisen in the individual user will be fixed in a single core that will prevent this problem for the potential emergence of other users of the system. Also, after implementation to the new system functionality, the system update will be available to all users simultaneously without requirements to install updates for each copy of the system. Centralized usage of the different system's data significantly increases and diversifies the training data for machine learning algorithms usage, which increases the accuracy of automated decision-making in situations that are not specific to the current system, but occurred in other systems.

SaaS systems structure

The architecture of intelligent house based on the SaaS model is the "client-server" architecture that consists of three main components: client side, provider server, data communication between client and server side. The client side of the system consists of sensors inside the house, the main client-side controller, and module of home devices control. House sensors include lighting sensors, water leaks sensors and gas sensors, motion sensors, temperature sensors, sensors of electricity usage. The main client-side controller consists of hardware, which is based on the microcomputer and the software installed on this hardware. The software part of the system client controller based on a modular architecture and consists of the following modules: module for sensors data collection, module of sensors data conversion, main controller module, system states storage and manual control system. Hardware house devices control module is able to send commands to the home devices using infrared signals throw wireless data transfer protocols such as Wi-Fi and Bluetooth. The hardware of the service provider consists of powerful servers that get all building sensors from connected clients and comply the requirements for large data processing and calculations for automated decision making using machine learning algorithms. Also, server-side includes a database for client homes sensor parameters storing to use these data as a training set for machine learning algorithms used in automated processes of decision making related to changes of house device settings according to the changes of home sensors parameters. The server-side software based on the technology for implementation of highly scalable web-services. Optimal technology for this role is NodeJS, which is successfully used by companies such as PayPal and LinkedIn. The working algorithm of the system based on SaaS model consists of the following steps:

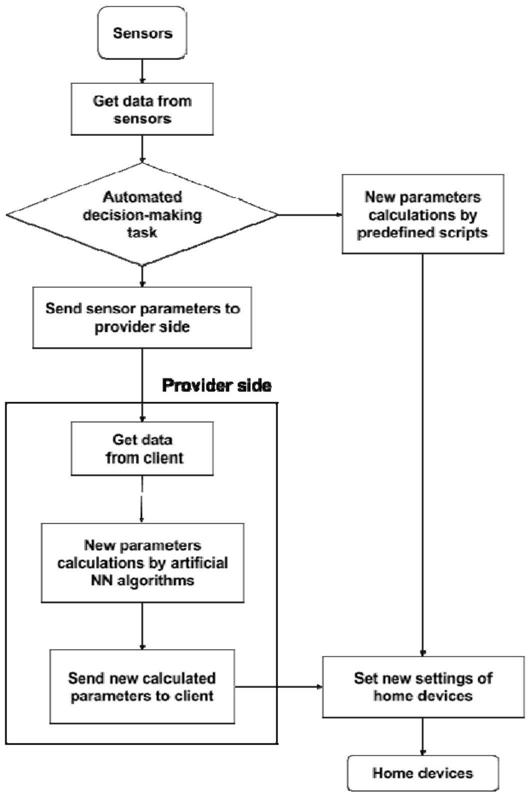

Fig.2. Scheme of local features and functions distribution in the cloud

After changes in the sensor parameters, information of the new sensor value is converted to the value from zero to one. This solution allows having all the values from different sensors in one measurement system. The client-side calculates the new parameters of home devices according to the changes of sensor parameters using predefined scripts, store the new state of the system and send commands to the home devices with new computed working modes of this devices. Changes if the system that needs computation on the server side, executes after a client-side request to the server according to a specified schedule. The client-side sends data to the server with the current state of the system (sensors parameters, device settings, time of the day, weekday, time of the year). Providers server-side send this data for processing to the module of automated decision-making in which with the use of machine learning algorithms that calculates the new state of the system with the new parameter values of the devices, which will be sent back to the client. In case of new system state that is different from the current state of the client, the system sends commands to the home devices with newly computed values of settings.

Risks of SaaS model usage

Along with the factors that push the customers to start using the software as a service, and push the developers - to invest resources in SaaS development, there are a number of constraints that limit the usage of this model. So, as the main resource of Saas-provider savings achieved by scaling, Saas is an inefficient model for systems that require deep personalization and adaptation to a specific customer. Also, many customers may fear to use Saas model in terms of security and potential leaks from the side of Saas provider services. Security issues, restrict the usage of SaaS-model systems that work with confidential information [16]. One other critical factor that limits the usage of this model is the requirement of the constantly working connection to the Internet. A partial solution for resolving of this problem is the use of modules for autonomous work.

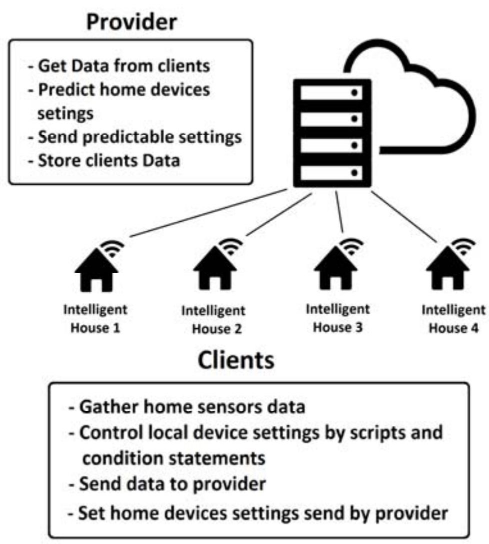

Fig.3. Functions distribution between client and server

Energy efficiency analysis based on SaaS model

The tasks that require large computation forces for storage and processing of large data amounts, which can be transferred to the provider side, includes tasks of automated energy losses analysis during intelligent house devices work. The main idea is machine learning algorithms usage that performed calculations of the optimal energy usage level for the current parameters, such as time of the day, the presence of people in the house, season, ambient temperature, and the list of turned on devices at home, such as electric kettle, TV, refrigerator, lighting, infrared heater. In certain periods of time, it makes calculations of the total power usage in the house and collection of all parameters which will calculate the optimal rate of energy usage for current settings. After calculations, the results are compared with the current real value of electricity usage. At high data difference values, the system will send messages to users on mobile devices or display it in the management interface of a smart house. The message contains information about the energy loses with a recommendation to check turned on devices (for example not turned energy save mode settings of the devices at night) to optimize electrical energy usage at home. For calculation of the optimal power rate for given home devices parameters, it is proposed to use machine learning algorithm, such as algorithm of the artificial neural network. The advantage of this solution is that the artificial neural network adjusts for power rate of devices commonly used at home, thus avoid entering the data manually for each given device and facilitates the calculation of electricity usage in the specific states of each device. For neural network training [17, 18], we need to use a dataset that includes parameters of electrical equipment of intelligent house and the summary electrical usage for current parameters, collected for a certain period of intellectual housework that was defined to collect training data. Example of training data used for neural network training is shown below:

Table 1. Training data example

Date	Time	Climat., mode	Kettle., mode	TV set, On/Off	Room lamp, On/Off	Sum. usage, Wh
4/9/17	09:00	5	3	1	1	166
4/9/17	12:00	2	2	0	1	68
4/9/17	15:00	2	2	0	0	37
4/9/17	18:00	4	3	1	0	74
4/9/17	21:00	5	3	1	1	166
4/9/17	00:00	5	2	0	1	72
4/9/17	03:00	3	2	0	0	80
4/9/17	06:00	3	3	1	0	134
...	...	...	...	...	...	...

Further automated calculation improvement of the results for the optimal usage of electricity occurs through interaction with users of the intelligent building. When users get a message about the current non-optimal rate of electricity usage, after the personal investigation and making a decision [19] about the absence of detected problems the user can add these parameters of home devices and corresponding total electricity usage rate to a training data for future similar situations. The structure of the neural network that used to determine the variation of electricity loses for parameters of intelligent house devices determined by experimental results [20]:

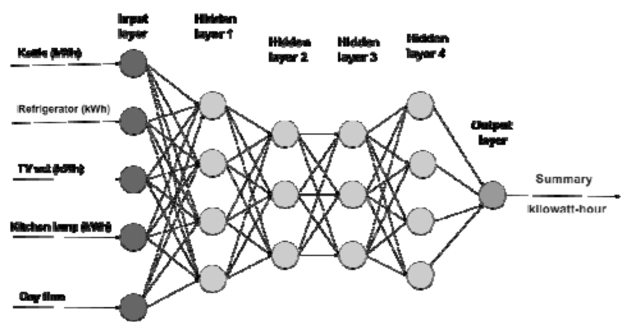

Fig.4. Neural network structure

Optimal electricity usage level chart calculated using an algorithm of the artificial neural network [21, 22] and real electricity consumption chart shows the periods of time in which was defined the non-optimal usage of electricity according to current parameters of home devices in every given moment of analysis:

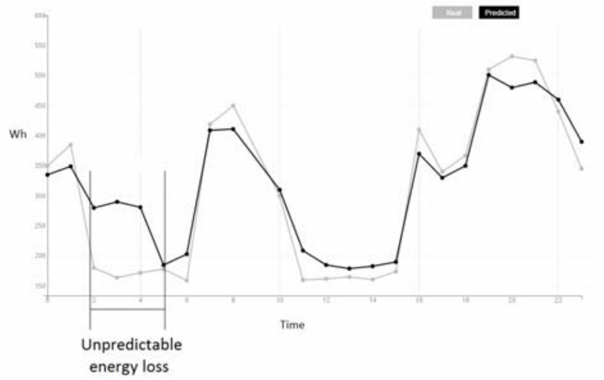

Fig.5. Power consumption chart

Storage of the electricity usage data related to settings of home devices and analyzation of this data in SaaS model is running on the provider side. This task is resource-intensive and does not need fast feedback, so switching of this functionality part to the provider side will optimize computation resources of system client side that will increase the performance of the whole system.

Conclusion

As a result of the current research was developed the smart house system architecture based on SaaS model, which is one of the most popular models of cloud computations, due to flexible opportunities to distribute the load between inexpensive client hardware and powerful provider server that can significantly improve the performance of the system, to facilitate the process of software maintaining and reduce the cost of equipment for the end user. Implementation of the proposed machine learning algorithms used for energy consumption optimization is the implementation of the intelligent house functionality, responsible for the automated energy efficiency management throw electrical house devices control based on the analysis of optimal setting modes of devices.

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