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Description	

Short-term prediction of energy consumption of air conditioners based on weather forecast

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***Abstract*— In residential houses, air conditioners consume a lot of electrical energy. In order to improve energy efficiency for residential houses, short-term prediction of energy consumption of air conditioners is required. In this paper, we propose the use of our thermal simulation to simulate the change of room temperature based on weather forecast information and predict the energy consumption of an air conditioner in a residential house. In order to calculate solar radiation heat flux, which contributes a lot to the change of room temperature, we utilize a neural network model to predict global solar radiation using training data obtained from weather stations. We also utilize a PID control model to simulate the operation of air conditioners. The accuracy of our simulation is verified by experiments carried out at a real testbed house.**

Keywords*— *Smart home; Home Energy Management Systems; Energy consumption prediction;

I. INTRODUCTION

With the development of computer and network technologies, a new paradigm of Internet of Things (IoT) that every thing around us will connect in a network gradually becomes a reality. In such an environment, information of physical space obtained by sensors can be sent into cyber space (i.e. computers), which computes the status of the physical space and optimizes the control of actuators on the physical space in order to reduce the operation cost of the whole system. Such kind of systems is called cyber physical systems (CPSs) [1] and attracts a lot of attentions of researchers. In CPS systems, the prediction of the behavior of physical space with the help of sensing data is required for control optimization. In the case of residential houses, which contain various types of electrical devices and energy resources, we may need to predict the amount of electrical energy consumed in a time period. The prediction result can be used, for example, to decide the optimal way of energy control [2-4] or to optimize control for thermal comfort [5].

Air conditioners are widely used electrical devices, which remove or add heat (i.e. cooling or heating) to rooms in order to change room temperature to adapt to user requirement of thermal comfort. An air conditioner is often one of electrical devices that consume the most of electrical energy in a residential house. Thus, precise prediction of energy consumption of air conditioners is essential for CPS systems in smart houses to improve energy efficiency.

Research on energy prediction for buildings has been done for a long time. The black-box modeling approach applies machine-learning techniques for energy consumption forecasting [6-8]. This approach is appropriate for commercial buildings for a long prediction period since it is easy to collect training data and energy consumption does not depend much on detailed usage scenarios. However, this is not the case of residential houses, where occupants may change their operation schedules everyday. Therefore, in this paper we focus on the white-box modeling approach, which estimates the energy consumption of an air conditioner of a residential house based on physical models.

The energy consumption of an air conditioner in a room depends on the amount of heat required to add or remove, which depends on the amount of heat fluxes coming in or going out the room. These heat fluxes may include the flowing elements.

- Conduction heat flux coming in or going out through a wall or a window. The amount of heat flux depends on the difference between outside surface temperature and room temperature and the structure of walls/windows.
- Solar radiation heat flux coming in through windows. The amount of heat flux depends on the diffuse radiation and direct radiation from the sun and the solar radiation heat gains of the window.
- Heat flux radiated from electrical devices and human bodies.

In order to predict the amount of electrical energy consumed by an air conditioner installed in a room, we need to simulate the change of the room temperature, calculate the amount of heat fluxes coming in or going out the room and simulate the operation of the air conditioner due to the change of room temperature.

We have built a thermal simulator, which calculates the change of room temperature by calculating the amount of heat fluxes at every moment by the use of offline data [12]. In this paper, we propose the utilization of our thermal simulation to predict short-term energy consumption of air conditioners. Our simulator gets input from weather forecast data measured by nearby weather stations. In order to calculate solar radiation heat flux, we utilize a neural network model to predict global solar radiation based on weather forecast information obtained from weather stations. We also utilize a PID control model to simulate the operation of air conditioners. We verify the performance of our system by experimental data measured at a testbed house. The simulation results show that our simulator can precisely predict energy consumption of air conditioner in a short-term period.

The structure of the paper will organized as follows. The next section shows the simulation model and the following section shows the model and the structure of our simulation. The simulation results are shown in section IV and the last section will conclude the paper.

II. Simulation model

A. Thermal simulation model

We assume that at present moment, we can get the status of the room and the outside weather condition by the use of sensors. Based on user schedule, we can obtain the operation time of air conditioner in a future time period. We then need to predict the amount of energy consumption of air conditioner in the time period. It means that if the air conditioner is turned on in the prediction period, we need to calculate the amount of energy that the air conditioner consumes during its operation. We consider the length of prediction period is within 24 hours since the usage period is often one day.

In order to predict the energy consumption of air conditioner in a time period, we need to predict the heat fluxes going out and coming in in the prediction period. These heat fluxes depends on the room temperatures, outside temperature, solar radiation and energy consumption of electrical devices in the room.

We utilize a thermal model, which calculates the change of room temperature based on a simple thermal model in which the change of room temperature depends on the total amount of heat fluxes going out or coming in a room as the following equation.

$$\frac{\partial T}{\partial t} = \frac{1}{C_v}\sum_i \beta_i Q_i(t) \qquad (1)$$

Here, $Q_i(t)$ are the i^{th} heat flux going out or coming in the room at time t and C_v is the heat capacity of the room. In our thermal model, the heat flux $Q_i(t)$ is calculated based on various physical models which specifies thermal characteristics of a room. However, even though document of home plans and specifications of a house can be obtained, these parameters are not often precisely determined. For example, when calculating solar radiation heat flux, parameters such as window area, solar radiation heat gains are required but solar radiation heat gain of a window depends on glass material, thickness and layer structure of the window which are rarely specified in house specifications. The coefficient β_i corresponding to the heat flux $Q_i(t)$ can be considered as a representative parameter for all uncertain parameters involved in the calculation of the heat flux $Q_i(t)$. We only need to estimate these coefficients, whose number is small, by the use of training data.

In short period, we can assume that the outside temperature is not changed lot. In a long period, this assumption is not correct anymore. In this case, we need to use weather forecast data to predict the change of outside environment.

Weather forecast data can be obtained from a number of Websites, some of which provide API for data acquisition. Information of weather forecast may vary from providers in data type, forecast interval. In this research we assume that our system can obtain hourly weather forecast data from a web service and the data include air temperature, humidity, precipitation, weather status (sunny, cloudy or rainny). Several Websites [18, 19] can provide such kind of services at present.

B. Prediction of solar radiation

Solar radiation heat flux is an important factor, which gives big impact on the energy consumption of air conditioner during daytime. Solar radiation heat flux coming in a room depends on solar radiation and the area and solar radiation heat gains of windows in the room.

Global solar radiation has two following components and we need both data to calculate the heat flux:

- Direct solar radiation, which comes directly from the sun down to the surface of the Earth.
- Diffuse solar radiation, which reaches the Earth's surface after having been scattered by molecules and particles in the atmosphere.

Since direct solar radiation has strong directional characteristic, it may only enter a room for a certain period of time during a day due to sun position and window direction. On the contrary, diffuse solar radiation is not strongly directed.

The data of direct solar radiation and diffuse solar radiation at the location of a smart house are not always available. In order to measure solar radiation, various types of measurement devices such as solar heliographs, pyranometer or pyrheliometer can be used. However, the cost of these devices is expensive and therefore they are not always available at the site of residential houses. For example, only a small number of weather stations in Japan have pyranometers, which measure global solar radiation. Other weather stations only have a solar heliograph, which measures sunshine duration only. Further, weather forecast data of weather stations does not contain information of solar radiation.

We need a method, which can estimate solar radiation at the site of a house based on weather forecast data obtained from a nearby weather station. From related works [8], global solar radiation can be estimated from various parameters including air temperature, air humidity, sun position, and the amount of cloud or sunshine duration. Further, direct solar radiation and diffuse solar radiation can be calculated from global solar radiation due to the work of [9]. However, though sun position can be calculated and we can obtain air temperature and humidity from weather forecast information, the amount of cloud or sunshine duration is difficult to predict and is often not included in weather forecast information.

Therefore, in this paper, we utilize a neural network model to estimate global solar radiation based on weather forecast information (Fig. 1). The inputs of our model are air temperature, air humidity, sun position (solar altitude, solar

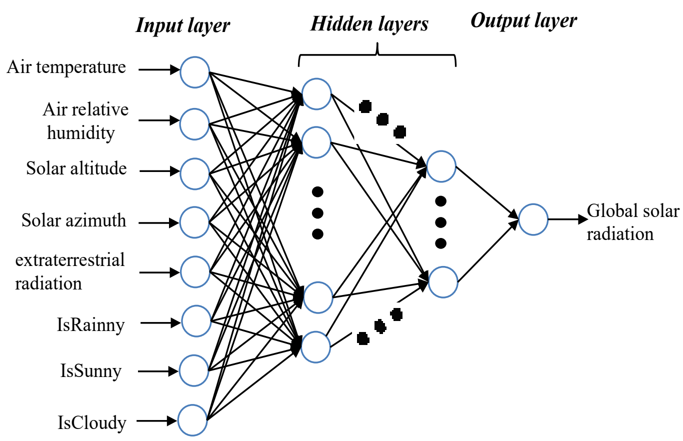

Fig. 1. Neural network model for solar radiation estimation

azimuth), extraterrestrial radiation and weather condition such as sunny, cloudy or rainy. These inputs are selected since it is easy to obtain the input data from the database of weather stations and weather forecast information. Solar altitude, solar azimuth and extraterrestrial radiation at the place of a house can be calculated by a function of both time and the geographic coordinates of the house [11].

The LevenbergeMarquardt algorithm is used as a training algorithm for the model.

C. *Air conditioner simulation model*

The operation of an air conditioner is complicated. Simulation models of air conditioners are proposed in several literatures but they require a lot of physical parameters, which are difficult to estimate. In this paper, we utilize a simple model to simulate the operation of an air conditioner.

There are two types of air conditioners, non-inverter air conditioners and inverter air conditioners. For non-inverter air conditioners, we can simulate them by two statuses: on and off. If the status is on, the air conditioner will output constant heat flux and thus we need to estimate the amount of heat flux that the air conditioner output based on experiment data.

For inverter air conditioners, we utilize a simple model of PID control to simulate the control of air conditioner. Due to PID control, we assume that the amount heat flux $Q_{aircon}(t)$ created by an air conditioner is calculated based on the following equation.

$$Q_{aircon}(\mathrm{t}) = \mathrm{K}_P \mathrm{e}(\mathrm{t}) + \mathrm{K}_i \int_o^t e(\tau)d\tau + K_D \frac{de(t)}{dt} \qquad (2)$$

Here, e(t) is the difference between room temperature and setting temperature. The parameters K_P, K_I, and K_D are the coefficients for the proportional, integral, and derivative terms of PID control and are estimated based on training data.

We then utilize estimated parameters to simulate the operation of air conditioner and predict electrical energy consumed by air conditioner, which are calculated by the following equation.

$$E_{aircon}(t) = \frac{1}{COP} Q_{aircon}(t) \qquad (3)$$

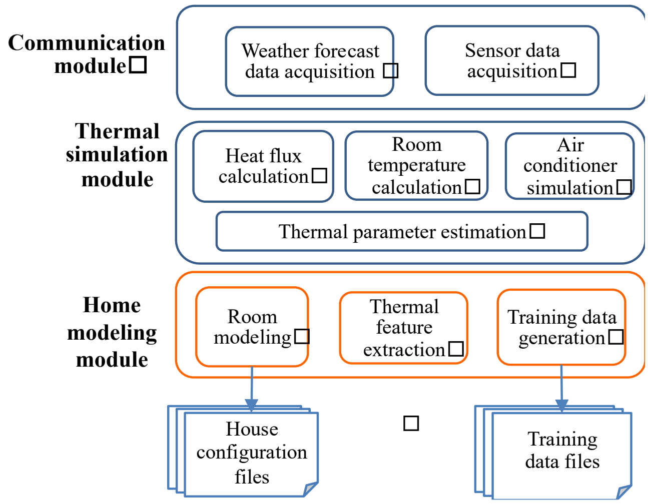

Fig. 2. Structure of thermal simulations

Here, COP is the Coefficient of performance of the air conditioner.

In the case the air conditioner is not active at the present moment, if the air conditioner is active in the prediction period, the PID control is initialized at the moment the air conditioner turns on. But if the air conditioner already turns on at the present moment, it means that the PID control of air conditioner is already initialized at a moment at past time. Since PID control also depends on the status of air conditioner in the past, therefore, we need to maintain the PID control's status to predict the energy consumption in this case.

III. SIMULATION STRUCTURE

We design a thermal simulator, which can predict short-time energy consumption of air conditioners by the use of weather forecast information. Our simulator gets present thermal state of the house based on sensor data and predicts the change of room temperature and the electrical consumption of air conditioner in a short-time period.

In order to do that, firstly we need to estimate thermal parameters in Eq. 1 from training data. Our simulator then uses estimated thermal parameters to perform online estimation by the use of sensor data and weather forecast data.

Our simulator will have three modules (Fig. 2).

- Home modeling module: models a house as a number of rectangular rooms adjacent to each other and each room contains a number of walls and windows. The module reads parameters related to thermal characteristics of walls and windows from a number of configuration files and creates an object to store the structure information of the house. It also reads offline environment data such as temperature, humidity, wind velocity, data of solar radiation as training data from sensor data files.
- Thermal simulation module: The module calculates the change of room temperature by calculating conduction heat fluxes, solar radiation heat flux and heat flux from air conditioner. This module also simulates the operation of air conditioner based on PID control. The module uses training data to identify unknown thermal parameters.

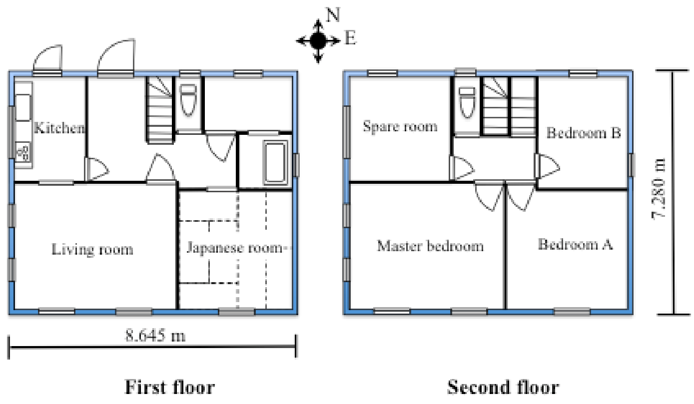

Fig. 3. Structure of iHouse

- Communication module: This module gets data from sensor installed in a house and gets weather forecast data from an online weather station. It then sends the data to the thermal simulation module to perform online prediction of energy consumption.

Our simulator will run in two modes. In background mode, thermal simulation module updates thermal status of a room and maintain the status of PID control of the air conditioner in the room based on real-time data sent from sensors installed in the house. In prediction mode, it obtains weather forecast information and operation schedule of air conditioners. It then calculates the change of room temperature based on the calculation of the amount of heat fluxes going out or coming into the room and the calculates the energy consumption of the air conditioner. The prediction mode is run in a schedule depending on the requirement of CPS systems.

IV. Simulation Results

A. Simulation environment

We implement Home modeling module and Thermal simulation module in MATLAB/Simulink, which is a very powerful program to perform numerical and symbolic calculations, and is widely used in science and engineering. We also implement Communication module in C++ so that it is easy to customize the communication interface with external servers.

We perform our simulation targeted on a real house called iHouse, which is a testbed for smart home services. The iHouse is located at Ishikawa prefecture, Japan (Fig. 2). It is a typical 2-floor Japanese-style house, which can divide into 15 rooms. Appliances in iHouse such as air conditioners, wattmeters and sensors are connected to the network via ECHONET lite protocol [17]. Most of the rooms in the house have one or more windows. The object of our verification is Bedroom A of the iHouse (Fig. 3). The air conditioner installed in the room is Toshiba RAS-281UDR, which is an inverter air conditioner.

There are a number of sensors installed outside the house to monitor external environment. They include a sensor for measuring temperature and humidity, an anemometer for measuring wind speed and direction and a solar heliograph for measuring actual sunshine duration, which is defined as the time that direct insolation is over 120W/m^2.

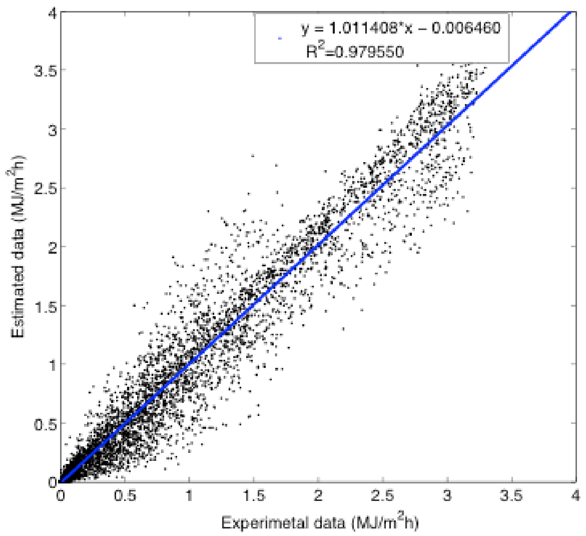

Fig. 4. Estimated data and experimental data of global solar radiation in the one-year testing period

In order to train neural network model for global solar radiation estimation, we obtain past weather information including hourly global solar radiation in the period from 2010/1/1 to 2015/12/31 at Fukui, Japan from the website of Japan Meteorological Agency [18]. We also obtain past weather information in the period from 2016/1/1 to 2016/12/31 at Fukui, Japan as the testing data for verification of the model.

In order to perform our thermal simulation, firstly we obtained training data from sensors installed in iHouse to estimate coefficient β_i corresponding to each heat flux Q_i in Eq. 1. In this experiment, the air conditioner was turned off. The training data was obtained during the period from 2017/05/28 to 2017/05/30. We then turned on the air conditioner and did experiments to obtain data from sensors for estimation of coefficients of PID control in Eq. 2.

We then performed our thermal simulation to predict the room temperature and air conditioner's consumption energy in 6-hour, 12-hour, 18-hour and 24-hour time periods. We utilized weather forecast information from the weather station located 16.4km from the house, which can be accessed from the website of Japan weather association [18].

In order to verify the result of the simulation, we saved the weather forecast data and perform the simulation in offline mode. We then compared the simulation results with measurement results.

In order to evaluate the accuracy of our simulation results, we calculated the following performance measures.

- Mean square error (MSE) and Relative MSE (RMSE) defined as

$$MSE = \frac{\sum_{i=1}^{n}\sqrt{(y_i - x_i)^2}}{N} \qquad RMSE = \frac{\sum_{i=1}^{n}\sqrt{(y_i - x_i)^2}}{N\bar{x}}$$

	MSE	RMSE (%)	MAE (MJ/m²h)	RMAE (%)
Training data set	0.031	5.91	0.092	17.40
Testing data set	0.030	5.49	0.091	16.67

- Mean absolute error (MAE) and Relative MAE (RMAE) defines as

TABLE 1. Estimation results of global solar radiation

$$MAE = \frac{\sum_{i=1}^{N}|y_i - x_i|}{N} \qquad RMAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{N\bar{x}}$$

where x_i and y_i are the estimated and measured values and $\bar{x}$ and $\bar{y}$ are the respective average values given by $\bar{x} = \sum_{i=1}^{N} x_i / N$ and $\bar{y} = \sum_{i=1}^{N} y_i / N$.
The next subsections show the results of our simulation.

B. Global solar radiation estimation results

We set the number of hidden layers of neural network model for global solar radiation estimation to be 15.

Fig. 4 plots the estimated results and measurement results of global solar radiation in the one-year testing period and Table 1 show the MSE, RMSE, MAE and RMAE of the neural network model. Although the value of MSE and MAE is small in both data sets, the value of RMAE is a little large (16.67% for testing data set). This error may become a source of error on our next simulation results.

C. Simulation results when air conditioner is turned off

The simulation results of room temperature when air conditioner is turned off are shown in Fig. 5. In this simulation, we utilize the weather forecast information to predict the change of room temperature in a time period of 24 hours. As the results, the mean deviation of predicted room temperature is 0.31°C while the maximum deviation is 0.78°C.

We also change the length of prediction period from 6 hours to 24 hours and compare the simulation results and measurement results. The longer the prediction period is, the smaller the deviation of room temperature is. In the case the prediction period is 24 hour, the deviation of room temperature is the biggest.

D. Simulation results when air conditioner is turned on

The simulation results of room temperature in the case the air conditioner is turned on are shown in Table 2. As the same of the simulation above, we change the length of prediction period from 6 hours to 24 hours. At the starting of the simulation, the air conditioner was already turned on.

We calculate the energy consumption in every hour and compare the simulation results and measurement results. When the length of prediction period increases, the difference between simulation results and measurement results increases. The values of MSE and MAE are small but the value of RMAE is big. There are several sources of error but the deviation of the prediction of solar radiation and the estimation of PID control parameters of the air conditioner may be a big source of error.

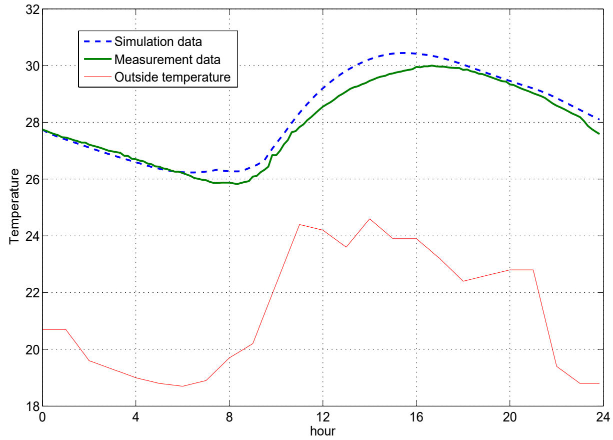

Fig. 5. Prediction results of room temperature in 24 h period when the air conditioner is turned off

TABLE 2. Prediction results of consumption energy when the air conditioner is turned on

Prediction period	MSE	RMSE (%)	MAE (kWh)	RMAE (%)
6h	$1.14*10^{-4}$	0.3	0.01	26.25
12h	$2.75*10^{-4}$	0.68	0.0136	33.65
18h	$9.29*10^{-4}$	1.66	0.0223	39.95
24h	$7.05*10^{-4}$	1.36	0.0178	34.41

V. REALATED WORKS

Prediction of transient cooling and heating requirements for buildings are essential to many applications, such as building energy management, performance diagnosis and optimal control. Detailed physical models or white-box model for buildings are used in a number of tools such as DOE- 2 [13], EnergyPlus [14], etc. for the early stages of building design but they require a large number of detailed thermal parameters to be specified. In the case of real houses, many parameters are unknown or uncertain and needed to be identified by the use of measurement data of external and indoor thermal environment. In our thermal simulation, we only need to estimate a small number of representative coefficients to fit the simulation results with measurement results.

Several black-box models [5-7] construct the relationship between input and output data based on neural network models. A building model is trained with experiment data to achieve accuracy. However, in order to achieve accurate predictions for a black-box model, a large amount of training data over a long period of time in widely varying conditions must be acquired. Further, obtained models may not respect the proper physics of houses. Therefore, if another model such as the model of air condition is required to add to the system, the new model must be trained again.

A number of works [14,15] use thermal network model, as a simplified thermal model, to calculate indoor temperature of a building. In this model, heat transfer through walls and windows is modeled as an electrical analog in which electrical parameters are calculated based on thermal resistance and capacitance of the wall material as well as the internal mass. Though the number of parameters necessary to estimate can be reduced comparing with detailed model, the number is still large. Further, a large amount of training data over a long period of time is still required to fit parameters of a model.

VI. CONCLUSIONS

In this paper we show our work on energy consumption prediction for residential houses. We utilize our proposed thermal simulation to calculate the change of room temperature and utilize a PID control model for the simulation of air conditioner operation. Weather forecast information obtained from weather forecast service provider is used as inputs to predict solar radiation. We also evaluated the accuracy of our simulations by doing experiments on a testbed house and comparing our simulation results and measurement results.

In the future, we need to improve the accuracy of solar radiation prediction results based on weather forecast information, in order to improve the accuracy of final forecasting result of energy consumption of air conditioners.

ACKNOWLEDGMENT

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