Multi-Agent based HEMS framework

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***Abstract*— Nowadays, smart homes have the goal of providing an easier and more comfortable lifestyle. For that purpose, smart homes contain a vast number of electronic appliances and consume electricity from the electricity grid or renewable energy sources such as solar panels. Smart scheduling of these electrical appliances to lower the consumed energy while keeping the residents satisfied is a complex problem. One solution would be the implementation of an intelligent Home Energy Management System (HEMS) that automatically determines the best schedule. The focus of this paper is the implementation of a framework that could facilitate the training of a smart HEMS, using Siebog a Multi-Agent based system. To ensure resident satisfaction, we propose a system that enables residents to define their priorities in a narrative form, e.g. "The dishes should be washed till 7 AM". Additionally, to provide smart and optimal energy consumption, as a part of the proposed system, we have implemented a cost function metric for machine-learning-based optimization that combines the two goals of resident satisfaction and lowering electricity consumption.**

I. INTRODUCTION

In recent years, the development and use of renewable energy sources has grown rapidly as a measure to combat climate change. To fully exploit the advantages of renewable energy sources further additions need to be made to existing energy distribution systems (such as large-scale energy storage and optimization of energy consumption). The problem of optimization of energy consumption can be addressed on different levels: the level of a single household or building or it can expand toward a larger population such as neighborhoods, cities, etc.

In this paper, we focus on the optimization of the energy consumption of a single household. From the viewpoint of the residents, the goal of household energy optimization is two-fold: lower the cost of electrical energy while ensuring a comfortable lifestyle (i.e. respect the expectations of the residents regarding the house temperature, availability of hot water, etc.).

Frequently, the grid stimulates its customers to minimize their consumption during the high-demand period or when the power supply reliability is imperiled. Thus, the cost of electricity may vary depending on the time of day. Consequently, the price of electrical energy can be significantly lowered by the smart-scheduling of appliances. This is a non-trivial problem that can be solved by the implementation of a smart House Energy Management System (HEMS). Smart HEMS represents an intelligent solution for managing energy consumption in a household [1].

The benefit of a HEMS system is the idea of automating everyday routines in a way that the time and energy are minimized, and the work is efficiently deployed during the day. Figure 1. represents a typical smart home that is powered by an electrical station and renewable sources and household devices that consume the electric energy. Our system is an implementation of a framework that can be used for training an Intelligent HEMS. Our system supports the following devices: refrigerator, boiler, air condition, washing machine, dishwasher, solar panel, battery, and uncontrollable devices such as entertainment. We have implemented a MAS (Multi-Agent based System) that will be used for training a HEMS that manages the previous devices.

For the simulation process, we use simulated data and real-world data. For example, the regulation of the house temperature in the Typhoon HIL simulation is influenced by the air conditioning, building thermal dynamics and external weather conditions. Here, Typhoon HIL is used to simulate the behavior of the air conditional system and building thermal dynamics, while the external weather conditions are the historical recordings of real-world data imported into the Typhoon HIL simulation. We also use real-world weather data in Typhoon HIL simulations of solar panel production of electrical energy.

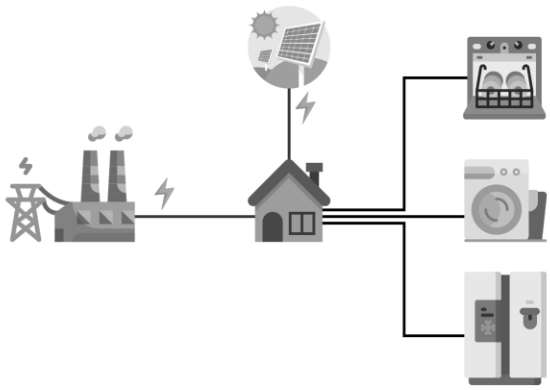

Figure 1. A smart home that consumes electric power from a power station (grid), a renewable energy source (solar panel) and household appliances.

A. Existing Solutions

The authors of [2] described an intelligent multi-agent system (MAS) for smart home energy management. The MAS is implemented in JADE framework and consists of agents for smart appliances (15 in total), SSM (Supply Side Management that manages power flow from the electrical supply systems: Solar Panel, Electric Vehicle, and Main Grid), and DSM (Demand Side Management, that manages the power flow to the appliances). The HEMS controls the DSM and SSM. SSM manages power sources and DSM manages appliances. The minimum time step is an hour of simulation time. The communication between agents is simulated, however, there are no smart home simulations or real-world consumption data to prove optimal energy usage. The decision making is based on simple predefined hand-crafted rules. The authors state that they have optimized the price, comfort, and peak reduction, but do not provide detailed experiments and results. Their focus in the paper is on developing an agent infrastructure for later experiments.

The authors in [3] describe a MAS that is also developed in JADE. The types of agents in this system are the same as in [2]. The minimum time step is an hour of simulation time. The energy consumption is prioritized based on the comfort level, where loads are sorted by predefined levels of priority. The user defines and sorts the priorities in a list, which can be cumbersome for the user to decide what is more critical, and importance can vary daily. The power consumption of each appliance is specified in advance, and the power demand and electricity price are calculated based on the constructed schedule. Authors prove their concept in a simulation of a single day. The simulation does not consider the availability of the load, e.g., is the washing machine filled with laundry before running it and whether the electric vehicle is parked at home when it should be charged according to the schedule.

In [4], the authors describe an embedded platform for the testbed implementation of MAS in building energy management systems. The simulation time step can be employed hourly or minutely. There are few elements supported than in a typical smart house (just the AC and illumination). To prove the developed concept, only one day is simulated from 8 am to 5 pm. The solution does not consider the modeling of residential wishes.

In this project, we consider the optimization of the energy consumption of a single smart home. Our use case contains a variety of household appliances, which includes:

- shiftable devices (i.e., devices such as the dishwasher which may be smart-scheduled by HEMS),
- devices that represent renewable energy sources (e.g. solar panel),
- electrical storage (ie., house battery), and
- loads which are must-run devices that are not to be controlled by HEMS (e.g., lighting and entertainment).

Our goal is to optimize both the comfort and the electricity consumption by training a model with the combination of simulated and real-world data. To this goal, we have implemented the MAS, which communicates with Typhoon HIL [6], used here as a simulation environment for schedulable smart home devices. MAS is used to calculate the cost function for a customizable period. Typhoon HIL has a controllable simulation step definition where the adjustable simulation step with the finest granularity of one minute. Our simulation considers the availability of the device.

II. METHODOLOGY

In order to optimize the energy consumption in a residence, we have adopted a two-fold cost function from [8] that simultaneously optimizes the goals of lowering energy consumption and respecting residential comfort.

There are two systems interacting with each other in order to evaluate the cost function: The Typhoon HIL framework and the MAS proposed in this paper. The Typhoon HIL application is used to simulate a schedulable device. Schedulable devices are controllable appliances (e.g., dishwasher, refrigerator, etc.), solar panel, house battery, and the power meter that controls power consumption from the main grid.

The Multi-Agent system that is used in this project is Siebog [5]. Siebog is a Multi-Agent middleware that consists of independent software agents. Agents can interact with one another through messages in order to achieve a common goal. Each agent has its defined task that will be completed in an intelligent way. Siebog consists of Agent Manager that has the task to take care of the agents' life cycle, Message Manager that takes care of the messaging between the agents via JMS, and WebClient that enables clients to create and start agents (Figure 2.).

Our solution (Figure 3) consists of device (load) agents that are classified into consumption agents that run and monitor the uncontrollable loads[1] and load shifting agents that control the shiftable devices (devices that can have a delayed activation e.g., dishwasher, washing machine). It also contains storage (battery) agent, and generator agents (solar panel and main grid that serve as energy sources).

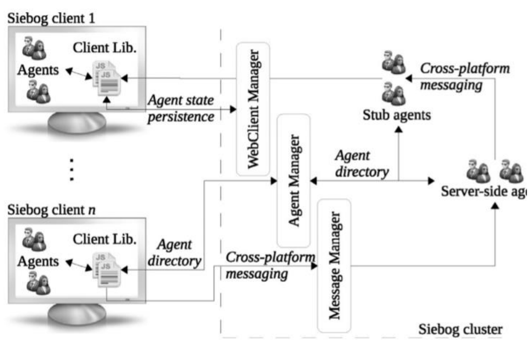

Figure 2. The overall architecture of Siebog multiagent middleware [5]

In the future, we are planning to develop an infrastructure that will be able to incorporate real-world data besides simulated data that is acquired from the Typhoon HIL. Typhoon HIL is an excellent tool for simulating the power consumption of the shiftable loads, the behavior of the house battery, and the main grid. However, it does not simulate residential behavior (uncontrollable loads) and relies on the outside temperature information to simulate solar panel energy production. For now, as a way of simulating real-world data acquisition in our setting, we have imported historical real-world data directly to Typhoon HIL (outside weather conditions and uncontrollable load consumption data). This data is represented with concrete values that are applied in the Typhoon HIL simulator.

[1] Here, uncontrollable refers to the fact that these loads are not to be controlled by the HEMS. Residents may choose to use these loads at any given time, and this action is not shiftable, i.e., it should be executed immediately. Lighting, cooking, and entertainment are examples of uncontrollable (must-run) loads.

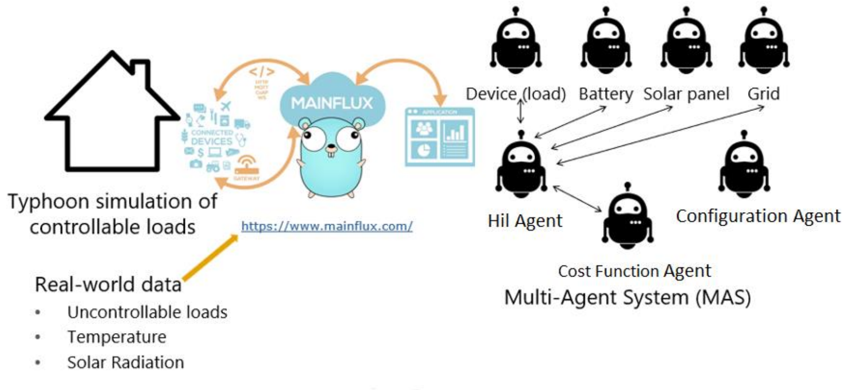

Figure 3. An alternative view on HEMS: Multi-Agent System (MAS)

The integration of real-time real-world data will be enabled through an open-source IoT platform Mainflux [7] (Figure 4). This will allow the integration of real-world data such as uncontrollable loads, outside temperature, solar radiation, humidity, etc. collected through sensors. In the final version of the system, the Siebog MAS will serve as a plugin for a real household system (data collected through sensors) instead of a simulated household system.

A. Cost Function

The cost function is the indicator of the efficiency of the household electrical energy consumption. In our framework, the cost function is evaluated for every performed simulation step. At the end of the simulation, the individual results are accumulated in an average result for a defined number of simulation steps.

We have adopted the definition of cost function from [8] that simultaneously optimizes the goals of lowering energy consumption and respecting residential comfort, as follows:

$$J = \sum_{t=1}^{T}\left[\left(\sum_{s=1}^{S}\text{benefit}_s(t)\cdot \mathrm{E}_s(t)\right) - C_{\text{electricity}}(t)\cdot E_{\text{grid}}(t)\right], \qquad (1)$$

where:

- T is the number of time steps in the simulation period,
- $S = 6$ is the number of energy services: air condition, boiler, refrigerator, dishwasher, washing machine, and “uncontrollable loads” (cooking, lighting, entertainment, and all other must-run loads are bundled together).
- $\text{benefit}_s(t)$ is the monetary benefit of having the service s during time interval t according to residential demands[2],
- $\mathrm{E}_s(t)$ is the demand for the energy equivalent of service s during time interval t (i.e., the energy spent [kWh] for running the service s during time step t),
- $C_{\text{electricity}}(t)$ is the cost of electricity during time step t. If the house is selling the electricity to the distribution grid, $C_{\text{electricity}}(t)$ is the selling electricity price.
- $E_{\text{grid}}(t)$ is the energy provided by the distribution grid during the time interval t [kWh]. That is, $E_{\text{grid}}(t) = P_{\text{grid}}(t)\cdot t$. Note that when the house is selling energy to the distribution grid, $P_{\text{grid}}(t)$ is negative.

The cost function depends on the value benefit of each device that is consuming electricity. The benefit is multiplied with the energy consumption by the device in the defined period. The electricity benefit for the currently working devices is summed and subtracted with the total energy consumption of all the working devices that depends on the tariff value. The tariff value varies depending on the time of day that the energy is consumed. These values can also be defined by a user.

III. Solution

In this paper, we focused on the development of a Multi-Agent System that can serve as a training environment for intelligent scheduling solutions (e.g. reinforcement learning). This will further have an impact on managing energy usage in households. We used Typhoon HIL to simulate the household energy consumption and production and we used Siebog to create agent instances that communicate directly with Typhoon HIL.

The simulation runs in 15 min time steps. Typhoon HIL simulates a 15 min scenario in a household e.g. turns on available devices, obtains the energy consumed from

[2] As in [8], we allow the residents to define the monetary value (i.e., the received benefit) for the provided service. For example, residents may be willing to pay a certain amount of money for the service of regulating the house temperature. We assign the monetary value to each unit of energy needed to provide the energy service during time step t. This monetary value corresponds to the residents’ perception of the importance of the service. Paper [8] explains how we may derive these monetary values by taking into consideration the electricity tariffs and narrative residential wishes such as “The dishes should be washed by 7 AM”.

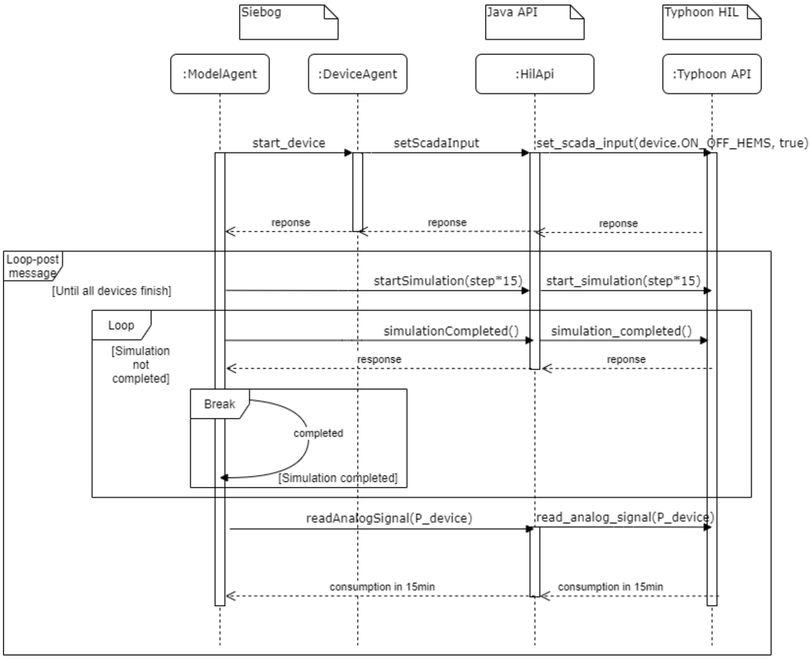

Figure 4. An UML diagram that explains the Communication Protocol between Siebog and Typhoon HIL application

working appliances, etc. Siebog verifies if the device was turned on successfully and what was the calculated energy cost and benefit in that 15 min step. After that, another 15 min simulation is started in Typhoon HIL and new energy consumptions are calculated.

The tasks are decoupled into the configuration, evaluation of the cost function, and device agents that perform a task related to different types of devices.

The configuration agent has the task of acquiring variable inputs such as variant tariffs during the day and monetary benefits of running individual devices. This data can be defined by the user. Tariffs vary depending on the time of day and they represent the electricity price of the grid per hour. Each device has its predefined benefit which varies depending on the time of day. For example, the refrigerator must keep food cool during the day, so the benefit is high all day. Whereas, a dishwasher will work only once a day and the preferred initial start would be at 7 am. The benefit is high at 7 am and is 0 for the rest of the day.

The configuration agent supplies the cost function agent with information regarding the value of the electricity price at the given time and the value of priorities of the devices that are currently in the HEMS system.

The device agents are individual agents for the devices that are in the HEMS system. Each device agent has the task to turn off or turn on a device in the simulation and provide the cost function agent with energy consumed in a time step.

The cost function agent evaluates the cost function which we plan to use to train a machine learning algorithm that will accomplish the task of managing household energy on its own.

Currently, our solution uses a single Siebog instance to represent a household with smart electronic appliances. Siebog is a distributed system and we can have more than one instance in a network where each Siebog instance could represent a residence in order to provide energy management on a larger scale.

A. *User-defined parameter values*

Here, we give a detailed explanation of the values used to define the different tariffs depending on the time of day (Table 1.), the monetary benefits that differ regarding the users' comfort (Table 2.)[3], and the users' priority for individual devices (Table 3.) used in our current implementation.

TABLE I.
TARIFF PRICES OF ELECTRICAL ENERGY

	Hours	Price
Peak electricity price	5 AM – 1 PM	0.4
Shoulder electricity price	1 PM – 11 PM	0.3
Off-peak electricity price	11 PM – 5AM	0.2

[3] As recommended in [8], the monetary equivalents are loosely based on the electricity tariff values (Table I). *High* price is chosen to be higher than the peak rate, which implies that these services should be delivered even during the peak period. *Medium* value is selected to be between shoulder and peak prices, which means that the medium-valued services may be curtailed during the peak pricing period.

TABLE II.
PERCEIVED VALUES OF ENERGY SERVICES AND THEIR ASSIGNED MONETARY COSTS

Importance	Value(€/kWh)	Description
High	0.8	The unit value of a highly valued service that should be delivered even during peak tariff price period. For example, the service of using a television during a highly anticipated show.
Medium	0.35	The unit value of a medium-valued service that may be curtailed. For example, the service of having hot water during the night when there is a low probability that the residents will need it.
Don't care	0	Residents do not care if the service is delivered or not. For example, residents do not care about the home temperature when they are absent.

TABLE III.
USER DEFINED PRIORITIES

Device	Hours	Importance
Refrigerator	All day	High
Washing Machine	13:00PM – 16:30PM	High
Dishwasher	1:00AM – 4:00AM	High
Uncontrollable Loads (tv, lighting, etc.)	During the day	High
Solar Panel	All day	High
Battery	All day	High
Air condition	12:00PM – 4:00PM	High
Boiler	8:00PM – 10:00PM	High

B. *Implementation*

Siebog initiates communication with the Typhoon HIL application (Figure 4.). Siebog loads the household model into the Typhoon HIL and starts the simulation.

Currently, we have implemented two base case scenarios that can serve as baselines for the intelligent HEMS algorithm which will be implemented in the future. In the first scenario, Siebog will start devices as soon as they are available. In the second scenario, Siebog will start the devices when they are available, and when running them results in the highest benefit.

The simulation runs for a predefined number of 15 min time steps. The simulation is started every 15 min of simulation time. Siebog reads the amount of electricity that each working appliance spent for the defined time and calculates the overall cost function. This cycle will repeat as long as there are working devices in Typhoon HIL and until the defined number of iterations is completed.

IV. CONCLUSION

Our solution defines a solid architecture for training an intelligent HEMS system. For example, it can be used for training a reinforcement learning algorithm. It is challenging to train a reinforcement learning algorithm using only collected real-world data, as this algorithm requires an interactive framework. Our solution provides such a framework. Moreover, in our simulated framework, we can simulate extreme scenarios such as prolonged power shortages, thus making the trained HEMS more robust. We could not hope to capture such situations in the real-world data as we cannot disrupt the lives of the residents to collect such data.

Our framework can also provide an insight on how different factors impact the overall cost of energy consumption in a household. Some of these factors are the time of day that the energy is being consumed from the main grid, different household appliances that are working, renewable energy sources that are in the system, and the end user's defined preference when a certain device is scheduled to work.

In the future, the current solution will be enhanced with additional features such as intelligence and security. Future work includes expanding the energy management problem on a wider and more complex grid as opposed to the current household management level. We plan on broadening our level of consumption management for buildings, neighborhoods, cities, etc.

Our main goal is to develop an artificial intelligence solution that will be trained with the help of our system with the purpose of personalizing user comfort and reducing the cost of energy consumption. By adding MainFlux to our system we will be able to expand our training data set with real-world data.

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