Energy Management Policies in Distributed Residential Energy Systems

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Abstract. In this paper, we study energy management problems in communities with several neighborhood-level Residential Energy Systems (RESs). We consider control problems from both community level and residential level to handle external changes such as restriction on peak demand of the community and the total supply by the electricity grid. We propose three policies to handle the problems at community level. Based on the collected data from RESs such as predicted energy load, the community controller analyzes the policies, distributes the results to the RES, and each RES can then control and schedule its own energy load based on different coordination functions. We utilize a framework to integrate both policy analysis and coordination of functions. With the use of our approach, we show that the policies are useful to resolve the challenges of energy management under external changes.

Keywords: Policy · Energy management · Coordination · Conflicts · Residential energy systems

1 Introduction

According to a recent annual energy outlook report by U.S. Department of Energy [1], the rise of residential energy generation such as solar photovoltaic (PV) capacity in the residential sector grows by an average of about 30 % year from 2013 through 2016. The rising cost of power generation, transmission, and distribution, together with the growth of electricity demand, is expected to produce an 18 % increase in the average retail price of electricity in the following decades. In fact, the deployment of renewable energy such as solar makes it possible to have a self-healing power system [2,3]. Through the use of more economic residential battery storage in the foreseeable future [4], energy management can be more efficient, e.g., power flow can be reserved during daytime to be used in the peak hours so as to reduce the peak demand from the grid. With the development of smart grid, it is desirable to not only manage energy from residential level, but also to integrate existing facilities with grid reliability and resiliency improvements [5] such as preventing power outage and handling power outage.

W. Li et al. (Eds.): IDCS 2016, LNCS 9864, pp. 121–133, 2016.
DOI: 10.1007/978-3-319-45940-0_11

We consider a network of residential energy systems (RESs) that is composed of several communities and each community consists of a small number of neighborhood-level RESs. Each RES is composed of a local energy storage, an inelastic energy load, and (possibly) residential energy generation such as solar PV. In such a network, external changes may occur, e.g., the electricity supply from the grid is limited due to the failure of a power substation or the heavy usage at other communities causes a low supply from the grid. Combined with the everchanging user requirements of different residences, it is important to control the energy load at both community level and residential level.

At the core of our approach is the policy analysis, which is used for the community controller to control the expected energy load of different RESs at the community level based on the external requirements. We propose three policies for the community controller to control the energy loads at RESs with no restriction on the power supply from the grid, with restriction on the total supply, and with restriction on the peak supply, separately. The policies are analyzed based on the predicted renewable energy generation and predicted energy loads of residences at the community controller and distributed to the RESs. Based on the results, each local RES controller can manage its own energy according to the user requirements by changing coordination functions. We employ a framework to integrate the policy analysis and coordination functions. In addition, we also provide a conflict resolution mechanism between policies.

Through the use of the policies and coordination functions, our approach provides an electricity management for each user that is adaptive to external changes. We present two use cases to handle the challenges in the RES network. The first case is to manage the peak demand at the community level in order to prevent power outage. This is achieved by managing the peak demand as a whole at community level and managing the peak demand of each RES locally at RESs. The second case handles a predicted power outage from the grid, where the community controller controls the maximum supply for each RES and RESs can adaptively adjust their local loads. Based on our simulation results, our approach is effective in managing energy loads at RESs to prevent power outage and handle power outage through energy prediction and scheduling.

2 Related Work

Open energy systems and residential energy systems that integrate renewable energy, energy storage, and communication technology have been studied and deployed [2,3]. With the use of communication technology, each residence forms an individual energy system that can support load control. We utilize the model of RES in our study and coordinate functions to adapt to external changes.

Residential energy management has been previously studied [6–11], mainly for the consumers to reduce the electricity costs by shifting electricity purchases according to different pricing model, e.g., real-time pricing, time of use (TOU) pricing, etc. Indeed, from the perspective of consumers, the management of the load can benefit the purchase of electricity. However, in addition to local residential load control, it is also desirable to integrate grid reliability and resiliency, e.g., to prevent power outage. A decentralized control algorithm of residential energy systems was proposed in [12] to balance the load of different residences so as to reduce the peak demand. In addition to the control problem in preventing power outage, we take a step further to use an adaptive framework and analyze through policies to handle various changes in the RES network.

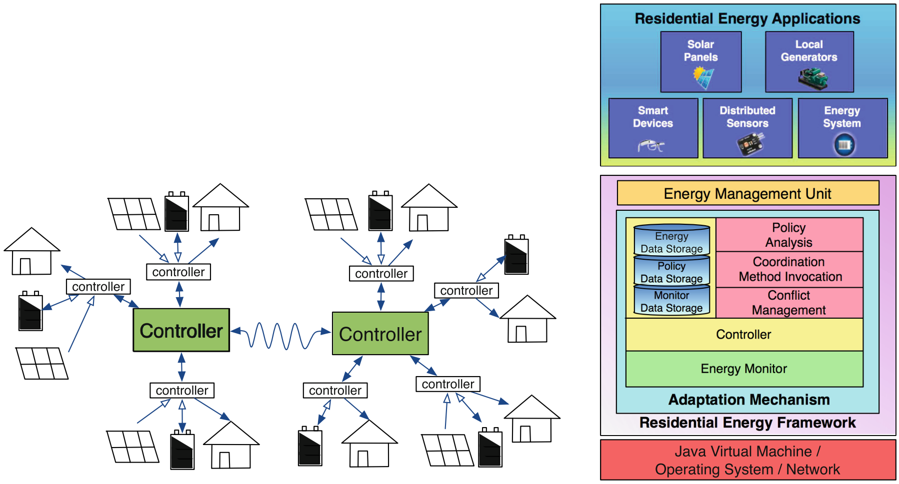
On the other hand, adaptive control of RESs have been previously studied, most of which focus on physical and network layers, e.g., adaptive dynamic routing protocols, or adaptive wireless or low-bandwidth communication links. An adaptive home/building energy management system was studied in [13] to control energy consumption by the convergence of heterogeneous network. Users in their system can freely configure a cooperative network of sensors and home appliances. Their main goal is to adapt to routing changes and ensure that the system operates correctly with heterogeneous equipments. However, they did not consider adaptive changes from the grid or the users for energy management. Coordination adaptation method, as we use for RESs, has been previously been studied. For instance, Bulusu et al. present a coordination-level approach to adapt to fixed environments [14]. Coordination via inter-process communication and synchronization can significantly increase the complexity of adaptation. Our approach, in comparison, separate external requirements at community level from user requirements as policies. Therefore, we can and reduce the complexity of coordinated adaptation and the data can be analyzed more efficiently.

3 RES Network

In this section, we first present the model of the RES network. Then we describe several challenges in energy management in the RES network.

3.1 RES Model

As shown in Fig. 1(a), we consider a network of residential energy systems (RESs) across several communities, where each community consists of a small number of neighborhood-level electricity network of several residences. Each residence has a residential energy system that consists of local energy storage (e.g., battery storage), an inelastic energy load, and possibly one or more residential energy generation (e.g. solar PV generation). The energy load is generated according to the requirements of the users in the residence. Each RES is connected to the electricity grid and can buy and sell electricity. We use a hierarchical controlling model for the RES network, where each RES has a local adaptive controller and each community has a central community controller. The community controllers at different community can coordinate with each other by sending and receiving messages and each community controller can control the energy usage of the community through coordinating functions in each RES.



(a) RES network. (b) RES framework.

Fig. 1. Residential Energy Systems (RESs).

3.2 Challenges

In the presence of changes in the external environment such as the restriction of the supply from the grid, it is challenging for control in energy management in the RES network. In this section, we describe two scenarios in energy management under external changes and their challenges in energy management.

Preventing Power Outage. The most desirable property is to prevent power outage. Since most residential loads follow similar pattern, i.e., they reach peak in the morning and during the night, it is desirable to reduce peak demand without large-scale capital costs. Decentralized control has been previously proposed [12], where each RES follows certain algorithm to cooperate with each other. However, there are various changes in the grid and in the RESs, e.g., the capability of the electricity grid handling peak load may increase or decrease according to the power generation and user requirements in the whole area, causing a change to the controlling strategies from the level of the RESs. Therefore, it is desired to control the energy load at both community level and RES level.

Residential Energy Management Under Power Outage. Modern infrastructure networks are becoming interdependent [15–17] where failures in a network may cause the failures in another network. For instance, if an earthquake is predicted in the area of nearby power substations, it is highly possible that the electricity grid can no longer provide enough energy to the residence for a period of time. However, since each RES may have locally stored electricity and renewable energy can be generated continuously, with prior electricity storage and scheduling, RESs can handle the power outage with the best effort.

4 Policy-Based Energy Management

In order to manage energy to handle the challenges described in Sect. 3.2, we propose a policy-based approach, where we build several policies for energy management at a community level. Specifically, we propose three policies in Sect. 4.1 to handle the cases where there is no restriction on energy supply, there is restriction on the total amount of energy supply, and there is a requirement on hourly peak supply from the grid, separately. Based on an analysis of policies, the results are distributed to the RESs in the community and each RES can control and schedule its own energy load based on different coordination functions, as shown in Sect. 4.2. We utilize a framework, as described in Sect. 4.3, to embed the policy analysis and coordination of functions. We also propose solutions to the two scenarios and resolve the challenges based on the proposed policies.

4.1 Policy Analysis

Policies are used to manage the load of each RES at the community level. In this section, we show three policies in our RES framework. Other policies can be added easily for various purposes.

We use a few notations to show the policies. We let n be the number of RESs in the community, $u(j)$ denote the predicted electricity usage for RES j, $g(i)$ represent the predicted electricity generation, and P be the maximum amount of electricity that can be purchased from the grid for the entire community, which is ∞ by default. The value of $u(j)$ and $g(j)$ are measured periodically. Without loss of generality, in the rest of the paper, we consider they are measured every day and represent hourly usage or generation. It can be observed that if $P + \sum_{j=1}^{n} g(j) \geq \sum_{j=1}^{n} u(j)$, there will be no restriction on the electricity usage in the RES network.

M-1: No Restriction. This is the default mode where each RES can schedule their load according to the user requirements. Users can take advantage of the real-time electricity price and schedule their loads according to their preferences.

M-2: Total Energy Restriction. In the case where $P < \sum_{j=1}^{n} (u(j) - g(j))$, some RESs will run under restriction on total electricity usage. For each RES j, if $u(j) > g(j)$, it is allowed to use $\frac{P}{n-t}$, where t is the number of RESs that can manage their loads with no restriction. For any other RES j, if $\frac{P}{n-t} \geq u(j) - g(j)$, $u(j) - g(j)$ is assigned to j, t is increased by one, and the rest users can share the rest electricity. This process continues until there is no user k that satisfies $\frac{P}{n-t} > u(k) - g(k)$, then $\frac{P}{n-t}$ is assigned to each of the rest RESs and the rest users cannot get enough electricity from the grid and must adjust their requirements where some appliances can no longer be scheduled.

M-3: Peak Demand Restriction. In order to reduce the peak demand of the community, the community controller first computes the predicted peak demand, e.g., per hour. If the demand D is higher than a threshold S, it simply assigns $\frac{S}{n-t}$ to each RES, where t is the number of RESs that generate more electricity than their demand. After receiving $\frac{S}{n-t}$, each RES shaves the usage of an amount of energy to other time if the demand is greater than the number.

4.2 Coordination Functions

Each RES receives the analysis results of the policies from community controller and it can schedule its own load locally. Based on different output of the policies, each RES controls its own load through different coordination functions. We propose the following functions in the RESs.

P-1: Prediction of Energy Generation. Assuming a RES has a PV for energy generation, combined with the weather forecast, the energy generation amount can be predicted. This can be a very useful function in residential energy management problems, i.e., for measuring $g(j)$.

P-2: Prediction of Energy Load Profile. Typically each residence has certain electricity usage profile. With certain prediction of events such as upcoming game days, the energy load may change. The prediction of energy load can be effective in preventing power outage, i.e., for measuring $u(j)$.

L-1: Load Management with no Restriction. Each RES has the function to manage their load by scheduling the appliances according to user requirements. This function assumes that there is no restriction on the amount of electricity that can be purchased from the grid.

L-2: Load Management with Restriction. This function schedules the load of appliances by considering that there is a restriction on either the maximum amount of electricity from the grid or the peak demand. Given the restriction, some appliances may not be scheduled or will be scheduled to other off-peak hours. Therefore, it requires that users also set up a priority of their requirements on the appliances that must be used, i.e., if some appliances must be rescheduled, the appliances with no priorities are first considered. There are several algorithms we can use. In this paper, we use a simple algorithm where minimum number of appliances will be affected, i.e., if x Watts are reduced from the predicted total demand, it always reduces the usage of the appliance that requires the maximum load until x Watts are reduced. In addition, in the case where peak demand should be reduced, appliances that can be rescheduled are first moved to other off-peak hours prior to the original scheduled time and then the appliance with the largest demand will not be scheduled.

4.3 Framework

In order to corporate the policies at community controller and coordination functions at RES controllers, we utilize a framework, as shown in Fig. 1(b). Our framework consists of two parts: an *Energy Management Unit* and *Adaptation*

Mechanism, the core of our framework. The former is responsible for collecting all types of data about user information. The latter is responsible for coordinating the invocation of functions to dynamically adapt to different changes through policy analysis. As observed in Fig. 1(b), our framework supports various electronic equipments, e.g., solar panels, local generators, smart devices, various distributed sensors, and energy systems. The data obtained by electronic equipments are aggregated into the *Energy Data Storage*.

We combine the external data[1] with the data of electronic devices in the RES, through which we can provide a predictive analysis for each RES. The core of adaptation mechanism is the *Policy Analysis* and we provide three useful policies to dynamically adapt to the changes in Sect. 4.1. The results of policy analysis are a set of plan tables for the RESs to manage the use of energy, according to different user requirements. In the extreme case, users may need to adjust their requirements for the framework to be resilient to failures. These analysis results are automatically saved into the *Policy Data Storage*.

In our framework, *Controller* has two roles: local RES controller and the community controller. Through communication between them, launching of the coordinating invocations can be decided. *Energy Monitor* monitors the changes in both external and internal of the framework in real-time. When the changes occur, we can change the coordination of the functions in the RESs through *Coordination Method Invocation* mechanism and we include a few coordination functions in Sect. 4.2. The *Conflict Resolution Management* provides a solution to resolve conflicts between internal electronic equipments and the external requirements of the users or applications, which may lead to serious problems.

4.4 Conflict Resolution

As mentioned in Sect. 4.3, conflicts may occur between the adaptation results and local RESs, e.g., some user does not follow the adaptation scheme, electrical appliances malfunction, or the external requirements change. In order to ensure the normal operation of our framework, we provide two kinds of conflict resolution for RES network to resolve both *local conflict* and *global conflict*.

When the electronic appliances malfunction or the users force to use some of them while they are not scheduled by the RES, the RES will not be able to achieve our executable policy's condition according to the output of the policies. In such cases, *local conflict* resolution will be executed. Our Energy Monitor regularly monitors the execution of policies of users. Once the energy monitor catches this conflict, our framework will send a message to controller, the policies will be analyzed by the community controller, and the results will be sent out and executed by RESs.

On the other hand, the conditions of the executable policies may not be satisfied due to the conflict between communities, which will cause *global conflicts* in our RES framework. In this case, the system administrators can use our

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[1] Currently, our framework only combines the external weather data to show the concept. More data can be combined to improve the accuracy of our analysis.

energy monitor to output the situation of the policy execution, locate the failed communities, and then modify their policies.

4.5 RES Energy Management

Based on above discussion, in this section we briefly introduce the flow of our approach in handling the challenges in Sect. 3.2.

Preventing Power Outage. As shown in Fig. 2, each RES runs either L-1 or L-2 to manage its load. Based on the weather forecast and user requirements, it also predicts energy generation and energy load profile for the next day. For instance, RES A and RES B both run L-1 where the load can be managed with no restriction and users can schedule their load according to the electricity price. The prediction of P-1 and P-2 are sent to the community controller from all the RESs in the same community. The community controller analyzes the results and run the policies. When there is a peak demand greater than the threshold P, the community controller distributes the demand of the users and limits some of them according to the policy, i.e., M-3. In this example, RES A will run L-2 after peak demand management where user A has to reschedule its load according to a restriction, some of the appliances may be scheduled to other time. RES B can continue running L-1 since its predicted load is lower.

Under Predicted Power Outage. When there is a predicted power outage, the workflow is similar with previous case. Namely, each RES still sends its predicted profile through P-1 and P-2 to the community controller. If there is a predicted power outage and the grid can only supply limited amount of energy to the community, the community controller analyzes the total amount of energy in the next day based on the predicted supply from the grid. Based on policy M-2, some RESs may be restricted with the maximum amount of electricity that

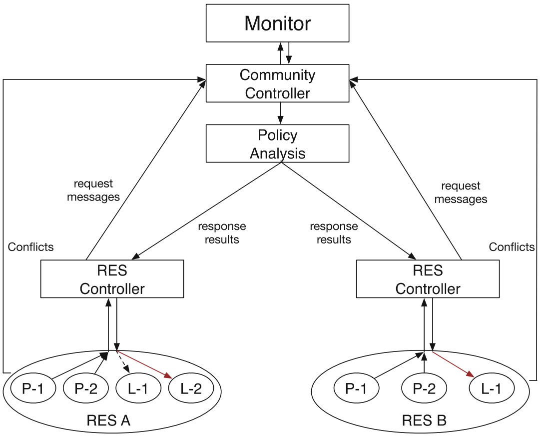

Fig. 2. Flowachart of RES network.

can be purchased from the grid. In this case, the RESs need to run L-2 with a restriction on the total amount of energy in the following day. Although some appliances may not be scheduled to run, users at each RES can still set priorities during the scheduling problem. For instance, it can set a priority to the usage of fridge, i.e., if there is a restriction on the total amount of electricity and some appliances must not be scheduled, other appliances will not be scheduled before fridge is considered. In this way, we both handle predicted power outage and build an adaptive solution according to user requirements.

5 Evaluation

In this section, we show the evaluations of our approach. We write a simulator to implement policies[2] on our framework. The RES controller and the community controller communicate through TCP channel as different servers. In this section, we focus on the effectiveness of our approach in handling external changes. To our best knowledge, most of previous work focus on the energy management at the residence level, which is not the main goal of our paper.

We simulate a community with 8 different residences with various elastic energy load. Each residence may have fridges, Wi-Fi, several lights, computers, smart phone chargers, TVs, hair dryer(s), a rice cooker, thermos, a microwave oven, a washing machine, and vacuum cleaner(s). In this paper, we use different rated powers for the same appliance at the residences to differentiate various brands. In addition, we use a mixed data of renewable energy generation where residences all have different energy generation and RES 5 does not generate renewable energy but it can purchase from the grid and store in its local energy storage. We evaluate the two cases in Sect. 4.5 and demonstrate the effectiveness of our approach to manage energy loads of the RESs.

Preventing Power Outage. We assess the case where the community controller controls the peak demand of the RESs using policy M-3. For simplicity, we ignore the amount of generated energy and assume each RES needs to obtain energy from the grid to show the performance of control on peak demand. As observed in Fig. 3(a) the total predicted demand of the whole community, the peak hours happen during the night between 19 to 22. We set a threshold for 10 kW and each RES needs to reschedule its usage if necessary. As shown in Fig. 3(b) a typical example, RES 4 in general has a high demand and it needs to reduce its demand at time 7, 8, and 20 to 23. We assume that fridge is set to a priority, wifi, lights, and computers can only be turned off instead of being scheduled to another time, and other appliances can be rescheduled. We observe that at most of the peak hours, lights and TVs are suggested to be turned off. The washing machine, rice cooker, thermos, and smart phones are rescheduled.

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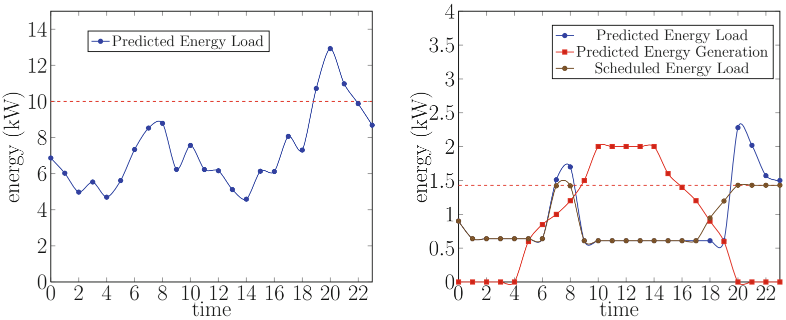
[2] Notice that two or more policies may specify different destinations under the same condition. The current implementation provides two solutions to solve local and global conflicts. However, in our existing implementation, policies are defined without any conflicts between them.



(a) Total predicted energy load of the community.

(b) RES 4 needs to reschedule energy usage to reduce the peak demand.

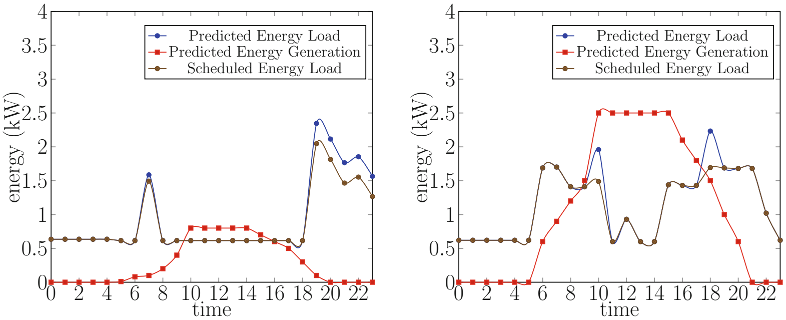
Fig. 3. Total predicted energy load of the community, where RESs need to reschedule their energy usage to reduce the peak demand.

As observed in the figure, the peak demand at the RES is reduced effectively according to the requirement.

Under Predicted Power Outage. We assess the case for a community to adapt to low power supply from the grid. We simulate the mode where the community controller uses the predicted data from the residential controllers to predict the usage from the grid. When the energy from the grid P is limited due to some factors such as the failure of a power substation, RESs must be controlled to reschedule their usage according to M-2. As summarized in Table 1 the total number of predicted energy load and energy generation, RES 6 generates more energy than the usage. This indicates that RES 6 can always support itself regardless of the amount of power from the grid. We limit the maximum amount of energy from the grid to 45 kW. The community controller runs M-2 and returns a result of power assignment to the RESs. As observed from the table, RES 1, 2, 4, 7 can obtain enough energy from the grid due to the low demand. However, RES 3, 5, and 8 can only obtain 6.43 kW from the grid due to the low grid supply. Therefore, they need to reschedule their energy usage.

Table 1. Summary of predicted energy load and residential energy generation and assigned energy (in KW).

RES	1	2	3	4	5	6	7	8
Energy Load	19.29	16.63	22.40	22.05	19.12	20.53	27.28	27.84
Energy Generation	13.02	10.51	14.38	20.85	0.00	21.60	26.20	20.40
Required Energy	6.27	6.12	8.02	1.20	19.12	0.00	1.08	7.44
Assigned Energy	6.27	6.12	6.43	1.20	6.43	0.00	1.08	6.43



(a) RES 3 where the lights must be turned off for 5.31 hours to reduce the total demand by 1.59kW.

(b) RES 7 where the rice cooker must be turned off for 1.26 hours to reduce the total energy by 1.01kW.

Fig. 4. Predicted energy loads, rescheduled energy loads, and energy generation.

The local controller of user 3, 5, and 8 can schedule their loads according to user requirements, i.e., with priorities on some of the appliances. If we set a priority, for instance on the fridge, it is possible that there is no solution to the usage. As shown in Fig. 4(a), with a priority on the usage of fridge, RES 3 requires 8.02 kW from the grid but is only assigned 6.43 kW. In order to reduce the usage of 1.59 kW, the optimal solution is to turn off the lights for 5.31 h. If there is no restriction, RES 7, as shown in Fig. 4(b), must turn off rice cooker for 1.26 h to reduce the usage by 1.01 kW. In all these cases, the appliances are turned off also to reduce the peak demand. In comparison, since RES 5 cannot generate energy, it is assigned 6.43 kW but requires 19.12 kW. In this case, there is no solution if the fridge cannot be turned off. If there is no priority on the appliances, the optimal solution is that the fridge must be turned off for the whole day and the computers cannot be used for 4.59 h.

Coordination Time. We show in Table 2 the coordination time of executing our defined policies. Each of the costs was the sum of the time interpreting the policies and message transmission to deploy the results. As observed in the table, the time interpreting the policies, in comparison, generates low overhead.

Table 2. Coordination time of policies (in ms).

M-1	M-2	M-3	Avg. Transmission
3.24	6.35	4.70	32.01

6 Conclusion

This paper presents a policy-based energy management approach in distributed residential energy systems. We present several policies for the RESs to adaptively manage their energy loads based on external requirements such as restriction on peak demand and limitation of power supply from the grid. Through the policy analysis at community level, RESs can manage and schedule their loads locally by invoking different coordination functions. We employ a framework to integrate the policy analysis and coordination functions. Based on the evaluation, our approach is effective to prevent power outage and to handle power outage.

Acknowledgment. Sisi Duan is supported by UT-Battelle, LLC under Contract No. DE-AC05-00OR22725 with the U.S. Department of Energy. The United States Government retains and the publisher, by accepting the article for publication, acknowledges that the United States Government retains a non-exclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States Government purposes. The Department of Energy will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan (http://energy.gov/downloads/doe-public-access-plan).

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