Mobile Cloud Networking for Efficient Energy Management in Smart Grid Cyber-Physical Systems

Neeraj Kumar, Sherali Zeadally, and Subhas C Misra

Abstract

Advances in mobile computing along with recent emerging technologies such as the smart grid and cloud computing are paving the way for a wide range of mobile cloud networking services and applications. In the smart grid cyber-physical environment, smart mobile devices communicate with the smart grid ecosystem via the control center, which plays a central role in selling and buying energy from smart grid users. The smart grid cyber-physical system can be viewed as a hierarchical architecture made up of a cyber plane and a physical plane. All smart devices reside in the physical plane, whereas in the cyber plane computing and communication resources are provided by the cloud server-based control center in smart grid. We propose an intelligent, energy-efficient scheme in smart grid cyber-physical systems using coalition-based game theory. All smart devices located at the physical plane are taken as the players in the coalition game. We developed a payoff function for each player in the coalition game based on transmission of information and service delays using conditional entropy for various smart devices at the physical plane. We analyzed the existence of the Nash equilibrium with incomplete information using various actions performed by the players in the game in the proposed scheme. Finally, we evaluated the performance of our proposed solution using performance evaluation metrics such as energy difference, overhead generated, and delay incurred.

Introduction

Mobile cloud networking (MCN) is an emerging technology in which mobile devices are connected to a cloud server using access points (APs) and gateways so that these devices can interact with the cloud server to access various services such as mobile healthcare, intellligent transportation, and entertainment. These services are provided to the mobile clients from cloud service providers located at different geographical locations. Cloud servers allocate resources such as available bandwidth, and storage to mobile clients as per their demands so that they can execute their applications in real time without any performance degradation. There may be several gateways in the MCN environment, which may be located at different geographical locations to provide connectivity and service availability to mobile clients. However, it may be possible that some of these gateways become overloaded or underloaded with respect to a large number of requests generated from different clients in a wide area network. Hence, intelligent decisions are required so that services requested by the mobile clients can be executed with respect to the number of available resources on the cloud.

Mobile devices are expected to participate in real-time energy trading using the MCN infrastructure. In this environment, smart grids (SGs) have emerged as modern electric grids with information and communication-based infrastructure capable of providing uninterrupted energy services to end users. Energy management has a direct impact on environmental issues where there is a need for the proper coordination among distributed energy resources (DERs) such as solar, hydro, wind, and thermal so that the energy generated from these resources can be sent to end users without delays. The energy generated from these resources needs to be distributed to end users by the control center in the SG in order to maintain a proper balance between demand and supply during peak and off-peak hours. For example, during peak hours, the energy stored in the battery of plug-in hybrid electric vehicles (PHEVs) can be used, while the electric vehicles can take energy back from the grid during off-peak hours, so the demand and supply can be maintained at all times in this environment.

As energy is one of the most valuable resources of the modern era, it needs to be consumed intelligently with proper coordination between service providers such as SGs and end users. The end users should use their household appliances based on the commands issued by the control center in the SG. For example, PHEVs can

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 1536-1284/16/$25.00 © 2016 IEEE

make intelligent decisions with respect to energy trading by selecting an optimal itinerary during charging and discharging processes [1]. During this process, PHEVs can make intelligent decisions on charging and discharging by receiving commands from the control center. In such a case, PHEVs act as DERs in that they behave as distributed power storage centers through proper coordination between the control center and the customers.

The energy used by various devices in the SG environment can be generated from different DERs, as discussed above. But intermittency issues associated with DERs may cause a performance bottleneck with respect to the energy generated and its usage in this environment. Hence, we need proper coordination between distribution and consumption of energy with respect to the customers' energy usage using an intelligent controller that can generate commands at regular intervals. This type of resource management, where the available constraints are taken into consideration from users' perspectives, is called demand side management.

SG can be visualized as the modern cyber-physical system in which all the devices can be located at the physical plane, and all the software tools used by the service providers are located at the cyber plane. The middleware located at the utility provider provides support to all the communication devices in this environment. This middleware ensures proper coordination between the cyber and physical planes so that various services can be accessed as per the users' demands.

A typical scenario for coordination between SG and the cloud is shown in Fig. 1. As this figure depicts, all the energy consuming devices are located at the lower layer. A local data collection unit (DCU) collects and transfers the data about power consumption to the nearest APs deployed in smart homes (SHs), as shown in Fig. 1. These APs reside in the utility domain where data is collected and processed by the utility company. As shown in Fig. 1, the collected data is sent to the backbone infrastructure followed by processing at the cloud-based infrastructure. As the data generated from different devices is collected in real time, the Hadoop distributed file system (HDFS) is used to process such a large number of different data streams in this environment. Generally, pricing details are communicated to all the clients every 10–15 minutes from the utility in consultation with the control center (i.e., the utility receives commands from the remote control center at SG). The utility is connected to the cloud control center using mobile gateways, which provide seamless connectivity to all mobile clients (PHEVs and smart devices are assumed to be mobile). The mobile gateways are also used for handoff and for the registration of mobile clients so that these clients can access various computing and communication resources from the control center. The SG control center resides in the cloud environment and generates instructions that are delivered to consumers at regular intervals about their electricity usage. Using the instructions obtained from the utility company, each user determines its electricity consumption schedule, which is in turn useful for the control center to make decisions about the energy management in this environment. As shown in Fig. 1, the energy inputs to the control center are provided by the various conventional and unconventional sources of energy in the SG environment. The energy generated from these resources is stored in the cloud data center where software as a service (SaaS) is used to cater for the growing demands of energy from various appliances residing at the physical plane.

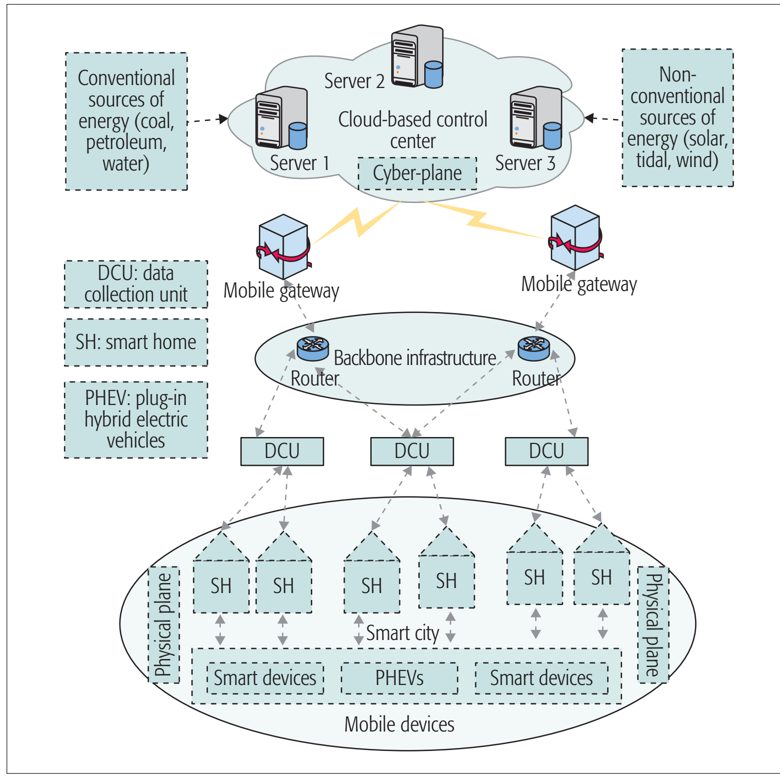

Figure 1. Interaction between cloud and SG.

Related Work

Mehar *et al.* [1] discussed the need for electric vehicles in the transport sector. The authors discussed the usage of various renewable energy sources and their applicability to the transport sector. Mondal *et al.* [2] designed a game-theoretic model for energy trading using electric vehicles in a mobile SG environment. The authors proposed a scheme in which PHEVs do not have to wait for charging from a single microgrid. Instead, they can charge from the coalition of microgrids without paying a higher price. The proposed scheme was found to be suitable for a distributed environment such as a cloud environment where energy trading between service providers and consumers exists. Mondal *et al.* [3] proposed a distributed dynamic pricing scheme for PHEV management in the SG environment. In their proposal, the authors introduced the concept of home energy and foreign energy management. A strategy is designed for managing the charging and discharging processes of PHEVs using a game-theoretic approach. Both of these schemes are applicable to the distributed cloud computing environment. However, these schemes do not compute and estimate price variations at the SG. A sudden change in the pricing policy at the

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grid influences the decision made by PHEVs for charging and discharging. Hence, with mobility of the PHEVs, price variation at the grid needs to be further investigated. Fang *et al.* [4] explored how the data collected from various smart devices in SG is processed using the cloud-based infrastructure. The authors have highlighted the advantages and identified the challenges in the SG and cloud computing environments. Other research proposals such as [10, 12] also exist in the literature where the authors explained the advantages of integration of SG and cloud computing. In these proposals, the authors described how demand response management is achieved using the integration of SG and cloud computing. Issues such as smart charging, load management, fleet of electric vehicles, and energy management are also described in detail in these proposals. However, these proposals do not discuss and explain how the integration between different devices located at different levels is achieved. In our proposed scheme, an adaptive forecasting scheme is used to compute the real-time pricing PHEVs use to make smart decisions with respect to charging and discharging.

Challenges and Constraints in SG-Based CPS

Various challenges need to be addressed to enable an efficient and cost-effective energy management in SG-based cyber-physical systems (CPSs). One of the challenges is efficient demand side management. Demand side management can be achieved in SG by making smart decisions with respect to the available energy resources and the demand generated from the end users at various time intervals. For example, users may indicate their energy usage pattern to the grid in advance, which the grid uses to make intelligent decisions with respect to power generation and distribution to the end users based on their consumption patterns. Second, optimal pricing of the available resources requested by the users should also be maintained from a user's perspective. In such a scenario, to meet the demands of end users, the pricing for the energy usage may be varied. Third, an optimal resource allocation framework that integrates the cloud computing environment for the smooth execution of various services is also required. Finally, the interoperability and efficient inter-cloud migration of various services need to be executed for high throughput and low delay.

The main research contributions of this article are summarized as follows:

- To address the challenges discussed above, we propose a new mobile cloud networking framework for efficient energy management in SG CPSs. Two types of planes (physical and cyber) are considered in the proposed scheme. At the physical level, hardware devices are considered, while at the cyber plane, various types of services and cloud-based infrastructure are included.
- Based on our proposed framework, a game is formulated between the smart devices (players) and the service providers (clouds) in which both players and service providers aim to maximize their profits with respect to the available resources.
- We also develop a new payoff function in the proposed scheme. This function considers the available number of resources and users' demands. Using this payoff function, each player in the game generates a bid for a particular resource to the service provider. Players compete among each other to maximize their benefits from the game.

The rest of the article is organized as follows. First, we highlight the system architecture for mobile cloud networking and describe the various components of the architecture. Next, we discuss the game attributes. We then analyze the Nash equlibrium (NE) with respect to incomplete information about the states in the game. We describe the interactions between the cyber plane and the physical plane along with the protocols used. Next, wepresent a performance evaluation of the proposed coalition game. Lastly, we make some concluding remarks.

System Architecture and Components

Figure 1 shows the basic architecture and components of the proposed scheme. At the lowest layer, there are various smart devices on which we have assumed that learning automata (LA) are deployed. LA are code fragments that have the ability to learn from their past behaviors. During this process, LA interact with an environment and receive feedback on all the actions they have taken. In our proposed scheme, we assume that LA act as the players deployed on the smart devices and have a fixed learning rate. The number of actions and fixed learning rate are used to compute the probability of all future actions to be taken by the players.

LA is defined as $\langle R, Q, T, \nabla, G\rangle$, where $R = \{r_1, r_2, \ldots, r_n\}$ is a set that contains all types of states and their representation in state space, $Q = \{q_1, q_2, \ldots, q_n\}$ is a set that contains all actions taken by an automaton, $T = \{t_1, t_2, \ldots, t_n\}$ is a set containing the feedback reeived from the environment, $\nabla : R \times T \to Q$ is used for mapping of state and inputs, and G is a function used for mapping of state and variables from the environment. More details about the LA and action probability vector can be found in our earlier solutions [3, 7]. Each automaton updates its action probability vector by taking feedback from the environment [2–9].

For reward:

$$x_j(n+1) = \begin{cases} x_j(n) + a(1 - x_j(n)) & \Big| \; j = i \\ (1 - x_j(n)) & \Big| \; j \neq i \end{cases}$$

For penalty:

$$y_j(n+1) = \begin{cases} y_j(n) & \Big| \; j = i \\ y_j(n) & \Big| \; j \neq i \end{cases} \tag{1}$$

where a is the parameter for determining the number of actions taken, and subscript i, j denote a specific action taken at any instant.

Figure 2 shows how the various components interact in the proposed coalition game when processing a large collection of data in the SG environment. In this figure, a game is first formulated among the players of the game in which all the actions are taken with some random probability by each player in the game. This is because for the initial stage all actions are taken randomly without any input from the environment. However, as the game proceeds, each player learns from its past experience and takes future actions using input from the environment, which is the cloud-based SG CPS. During this process, the action probability vector is also updated with inputs from the environment. For example, inputs may be issued from the cloud-based SG CPS about the energy consumption by smart devices. During this process, each smart device may be involved in energy trading (selling and buying energy from the grid) from the SG.

According to the inputs received from the environment, each player performs actions such as pre-processing, analysis, and correlation of the results obtained in the proposed coalition game. A time series analysis model is used for energy forecasting and data processing in the proposed solution. Based on the past actions taken by other players, players learn from the environment using a known learning rate ξ. The value of ξ is taken as a constant in the proposed solution. For the first step, the raw data collected from smart devices is passed through pre-processing steps where alignment of the data is done. The conditional entropy-based analysis is used for different types of data to place each data type into different classes represented as various nodes in the Bayesian networks. A Bayesian network is one in which nodes and their associated transitions are represented as a directed acyclic graph, that is, random variables and their conditional dependencies are represented as a directed acyclic graph. Once the data is classified into different classes, it is correlated, and final regression analysis is performed to produce the final results. The resulting output is used as an input to LA, which will take all future actions in subsequent iterations. After a finite number of steps, the solution eventually converges to a finite final result. During this process, the analysis with respect to the usage of distributed energy sources such as hydro, PV panel, solar cells, wind, and thermal is also done. Moreover, LA coordinate the energy production of various types of DERs for optimal scheduling of energy usage of various smart devices in SG-based CPSs so that energy balancing can be done effectively. A more in-depth discussion of the steps is given in the following sections.

Payoff Assignment and Game Attributes

The detailed architecture of the proposed LA-based scheme is shown in Fig. 2. In this figure, we assume that the PHEVs on the road are divided into various clusters. We also assume that these vehicles may form a coalition among themselves to remain in a particular cluster for some time. Clusters are formed only to reduce the complexity of the mechanism as all the decisions with respect to cluster formation and restructuring are made by the respective head of the cluster in the proposed scheme. The coalition among the players of the game is established based on their payoff function (PF), which each player gets after performing actions with respect to charging and discharging in this environment. As the environment is highly dynamic in nature, a coalition needs to be built in such a way that it remains stable for some finite duration such that players can perform various actions with respect to data analysis in the game.

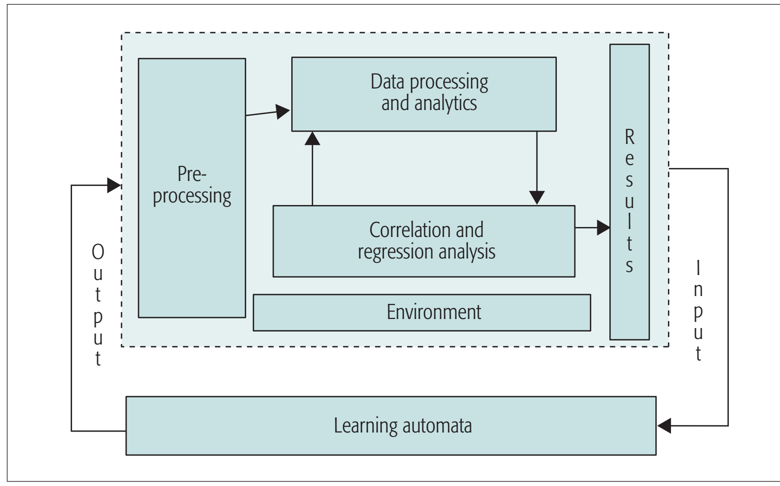

Figure 2. Components used for processing data in the proposed coalition game.

Definition 1–Entropy: It measures the skewness in the samples (i.e., how much is the uncertainty with respect to the sampling of the data).

Forecasting a Player's Behavior Using Conditional Entropy

Energy management is one of the most difficult tasks to perform in the SG-based CPS with support from the cloud. Based on the past behavior of consumers and usage patterns for various appliances in an SH, forecasting future behavior is achieved in the proposed scheme. The inter-dependences between different usage patterns of the consumers are modeled and represented using the conditional probability in Bayesian networks. Conditional probability is the probability of an event happening with the condition that an event has already occurred with a known probability. In the proposed scheme, we have modeled the past usage behavior of the consumer as a Markov decision process in which all the states and their associated transitions from one state to another are bounded by the conditional probability. Using the past usage patterns of all the users in all SHs, an entropy-based time series analysis is done in the proposed scheme. In the entropy-based time series analysis, we started with random sampling of the collected data from the users. Then an initial entropy is calculated based on this sample using the following equation,

$$E(X|Y) = \sum_{i,j=1}^{n} p(x_i, y_j) \log \frac{p(y_j)}{p(x_i, y_j)} \quad (2)$$

where $E(X|Y)$ is the expected probability of an event X occurring subject to the condition that event Y has already occurred. Also, $p(x_i, y_j)$ is the combined probability of a random sample from set X, Y, and $p(y_j)$ is the probability of an event from set Y. The conditional entropy defined in

After forecasting the player's behavior using conditional entropy measurements, an initial coalition is formed among the players of the game using incomplete information of the other players' moves for energy trading from the control center. This may generate additional overheads.

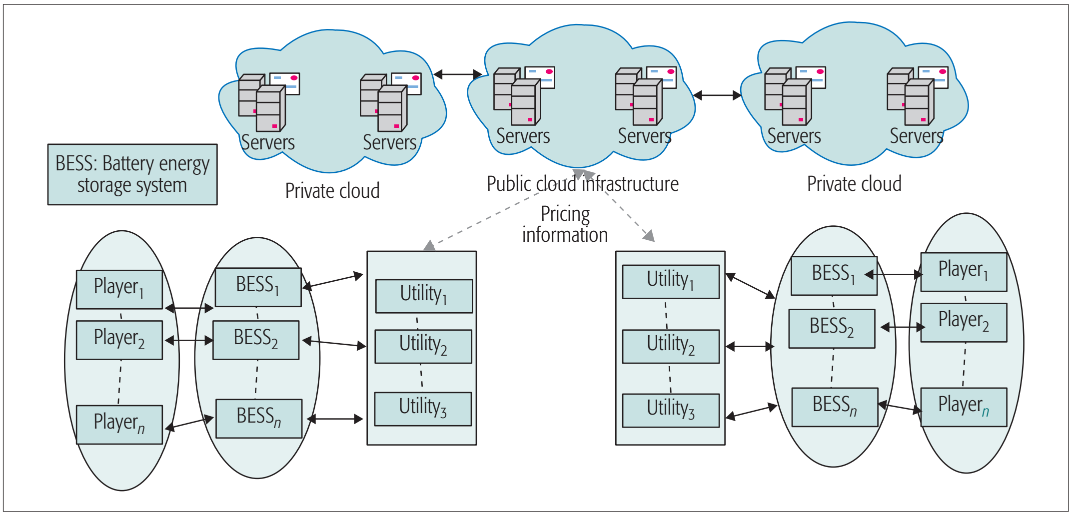

Figure 3. Pricing information and controller in coalition game.

Eq. 2 indicates that if we know the previous values of the data samples, we can predict future values using the conditional probability values in the given samples.

In addition, we have used the Markov decision model for state space representation of the players and their actions using the initial conditional probability. *PF* of each player is defined as follows:

$$PF = \frac{1}{n}\left(\frac{\delta E(X|Y))(cost - revenue) \times n^{rew}}{n^{pen} \times \delta(D^{trans} + D^{serv})}\right) \quad (3)$$

The future energy consumption of users is computed using Eq. 3. In this formula, n is the number of samples taken for future energy consumption prediction, and n^{rew}, n^{pen} are the number of rewards and penalties obtained by the players in the game. D^{trans} and D^{serv} are the transmission and service delays as information moves from the physical plane to the cyber plane. *Cost* and *revenue* are the cost associated with maintaining the resources and overall revenue/profit generation with respect to the service provision of the resources allocated to the players in the game. Also, $\delta E(X|Y)$ is the conditional entropy changes with respect to the initial and final values of the sampled data. After computing the initial entropy, the future entropy is computed with respect to the energy consumption by the players. After computing the past energy consumption by the users and predicting the future energy consumption, the difference δ from the mean of predicted and actual energy consumption is computed to determine the difference between demand and supply with respect to the current available resources. This forecasting is used to design an adaptive strategy for energy consumption by the players in the proposed coalition game. Moreover, in this coalition game, all unwanted samples are removed after normalization with respect to the entropy deviation from the mean value of all the samples collected. Hence, by estimating the past behavior of players and their current energy consumption, their future energy consumption is computed in the proposed coalition game.

Each player's actions are taken as input in the game. Players and their actions are represented in the Bayesian network with the conditional execution of various actions with respect to the deviation from the mean value of *PF* as defined by Eq. 3.

Coalition Formation with Incomplete Information about the State of the Game for Energy Trading

After forecasting the player's behavior using conditional entropy measurements, an initial coalition is formed among the players of the game using incomplete information of the other players' moves for energy trading from the control center. This may generate additional overhead with respect to the maintenance of different states and moves of the players. The advantage of making the coalition is that multiple players in the same coalition can generate a common *bid* for the energy from the control center to reduce the complexity in terms of the large number of transmissions from the physical plane to the cyber plane. The procedure for coalition formation and update is as follows.

Initially, all the players have equal probability of making a coalition with one another. As players do not have information about the state space, based on the *PF* defined in Eq. 3, each player's behavior is identified. By forecasting the behavior of each player in the game, an initial coalition is formed among the players of the game using the current *PF* of the players. But as the game progresses toward equilibrium, actions such as charging and discharging are performed by the players staying at the physical plane. Based on their actions, they may get feedback from the environment, which helps them to take all future actions.

The size of the coalition also changes with each move made by the players in the game. Each player has the flexibility to move from one coalition to another with an intention to increase his/her PF to obtain maximum benefits from the game. The proposed coalition game is viewed as the bidirectional flow of energy in such a manner that each player participates in energy trading by selling and consuming energy from the control center.

Dynamic Pricing and Payoff Function Variation

Pricing plays a vital role in efficient energy management at various levels in the SG-based CPS. Pricing can be static or dynamic based upon the participation of the players in the energy trading from the control center in SG. With a static pricing policy, the price of the energy consumption by the players is fixed during peak and off-peak hours, while in the case of dynamic pricing, the price of energy varies according to peak and off-peak hours. Compared to static forecasting, dynamic forecasting is used for real-time price information for the players so that they can make decisions about charging and discharging at any instant. In the proposed scheme, we have considered a dynamic pricing policy such that the players in the game make intelligent decisions with respect to charging and discharging from the grid as per their requirements. We have taken an interval of 15 seconds [14] after which the utility announces the current energy price, which can be used by the players to decide whether they will participate or not in the decision making process at various stages in the game. For example, if the price is high at any instant, only a small number of players participate in the coalition game. In this case, each player discharges his/her stored energy to earn maximum benefits. On the other hand, players charge during off-peak hours so that stored energy can be utilized at later stages. In such a scenario, a distributed battery energy storage system (BESS) is used by the players to store the excess energy taken from the grid. A BESS is used at a later time when energy becomes scarce during off-peak hours. A BESS is the collection of a finite number of electric batteries used to provide a power system. During peak and off-peak hours, these batteries are used to provide power to the grid to make it stable.

Figure 3 illustrates the interactions between the different components of the proposed system for supporting efficient energy management. As shown in the figure, the players participate in the coalition game with additional energy storage at the BESS. There is coordination, with respect to the decision taken between the players and the utility, about energy management in which the utility communicates to the cloud server-based control center for energy trading. The cloud-based control center residing in the public cloud infrastructure is connected to private cloud domains for proper coordination. If there is an excess energy load with respect to the job execution on the private cloud at the respective location, it may be shifted to the public control center so that real-time information about the job execution can be sent to the players for making correct decisions in the game. The information about the power resources from the private cloud at the respective location is sent to the control center, which computes the available resources and the demand generated at any instant of time. By making use of the players' behaviors and adaptive forecasting, the control center generates a real-time price of the power, which can be used by the players to make intelligent decisions with respect to charging and discharging from the grid. The grid, in turn, generates revenue by providing the power for a finite duration to the players at fixed or variable price depending on the current load, season, and requirements generated by the players. Thus, the proposed coalition game can be viewed as a bidirectional flow of power between the grid and the players with the ultimate objective of matching energy demand with supply as closely as possible.

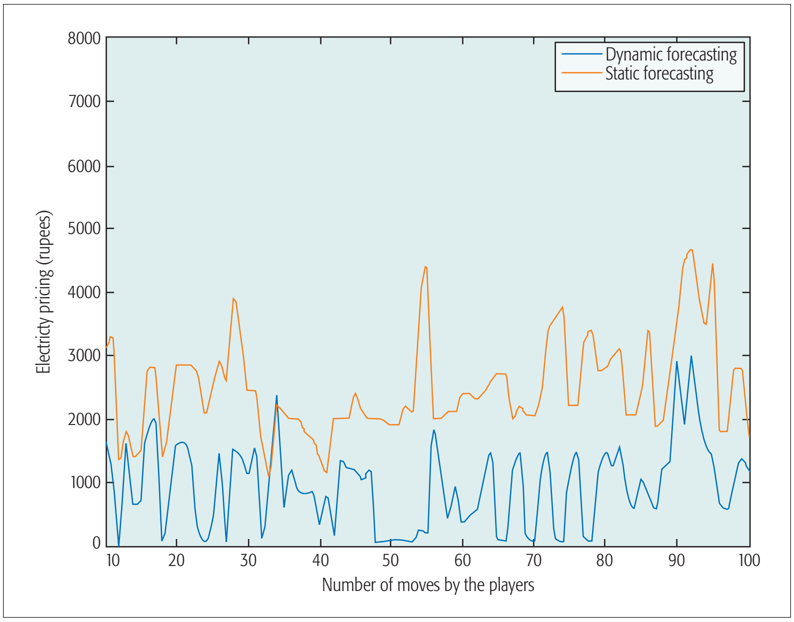

Figure 4. Pricing variation in coalition game.

Figure 4 shows the variation in the electricity price with the number of moves made by the players in the game. Figure 4 shows that with static forecasting, the electricity price increases more compared to dynamic forecasting. This is mainly because in dynamic forecasting, the players have better knowledge about the current electricity price and the available resources, which allows them to make intelligent decisions with respect to charging and discharging in the proposed coalition game. Hence, the electricity prices are better controlled in dynamic forecasting compared to static forecasting, as shown in Fig. 4.

Nash Equilibrium with Incomplete Information

Nash equilibrium is the condition where each player is provided a fair chance to execute all the actions in the game, that is, all players can make decisions with respect to charging and discharging to get maximum benefits from the game. The proposed coalition game consists of attributes such as strategy space, PF, n^{rew}, n^{pen}, and current state of the game. The strategy space consists of all the moves made and to be made by the players in the game. The current state of the game is modeled as a two-dimensional matrix in which all the players and their moves are represented using conditional entropy as defined in Eq. 2. As illustrated in Eq. 3, players and their transitions from one state to another are represented as a Markov decision process with conditional entropy in the proposed coalition game. The proposed coalition game is assumed to be non-cooperative in that players do not know the strategy space and the actions made. Based on the current state and *PF* of each player in the game, the players are allowed to perform the actions of charging and discharging from the grid.

Efficient decisions need to be made in the proposed coalition game so that energy trading can be done with an awareness of the current state of the grid, and thus it can be stabilized with respect to generation and consumption. Hence, in the proposed coalition game, initially only those players whose *PF* is higher are allowed to perform a finite number of actions so that they can participate in charging and discharging at the grid. The state of each player is updated according to the updates in the action probability vector.

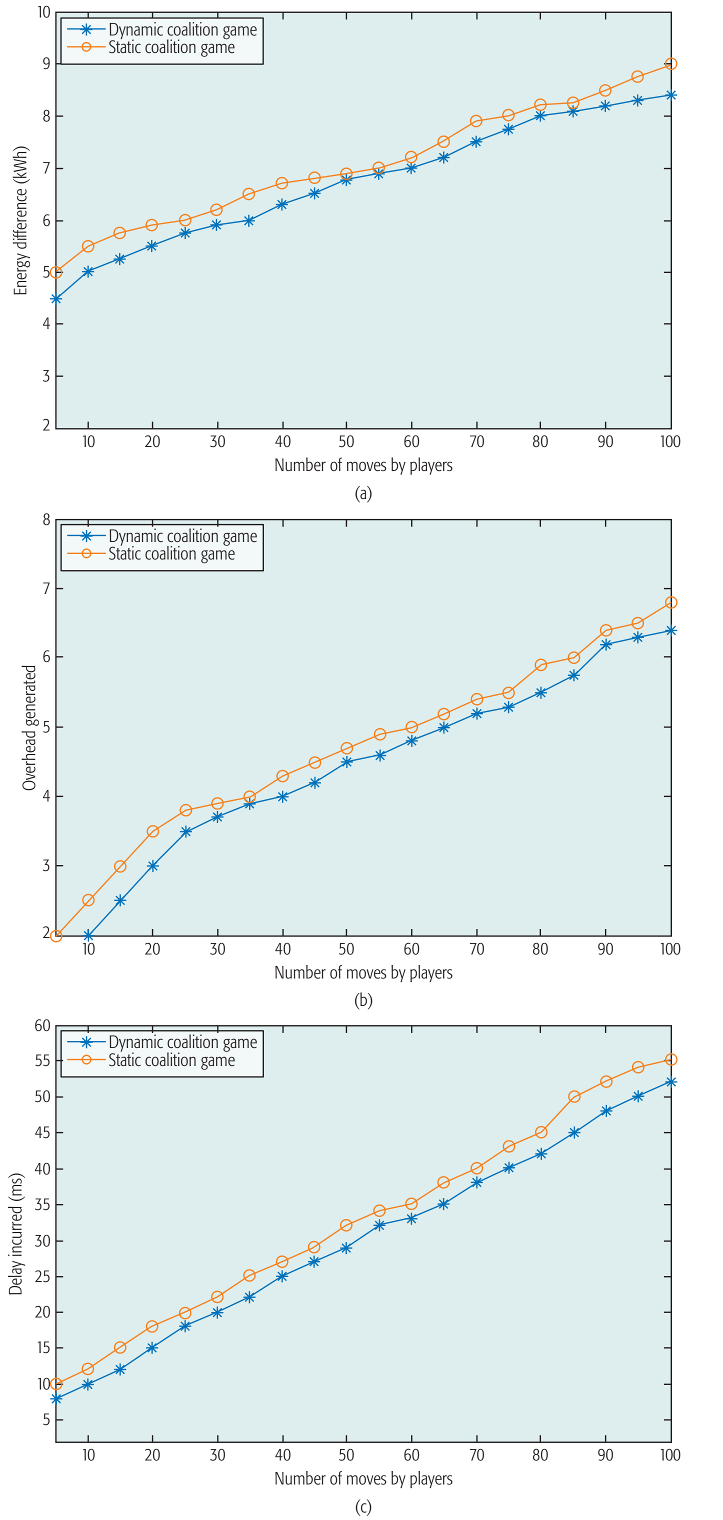

Figure 5. Variation of moves by the players with: a) energy difference; b) overhead generated; c) delay incurred.

Interaction between the Cyber Plane and the Physical Plane

The key component of the proposed coalition game is the interaction between the cyber plane and the physical plane so that control signals can be sent to the players in the game located at the physical plane. Using the control signals sent from the cloud-based control center, the players located at the physical planes make intelligent decisions with respect to charging and discharging at various stages (as shown in Fig. 3). All smart devices located at the physical plane send their requests for charging to the nearest utility in their locations that provides services to them as per their demands in consultation with the control center. Utilities located in different geographical locations are interconnected with each other using the backbone architecture where various routers and layer 2 switches are deployed. All decisions with respect to routing and fault tolerance are made at the backbone architecture, which is constructed using networking technologies such as wireless mesh networks (WMNs) because of their cost effectiveness and self-healing nature. Finally, the backbone is connected to the cloud-based infrastructure using various gateways in different regions. Various types of medium- to long-range communications are also used for communications between the physical plane and the cyber plane. For short-range communications, Bluetooth and RF identification (RFID) are used. For medium-range communications, IEEE 802.11 a/b/n and Wi-Fi are used, while for long-range communications, WiMAX and Long Term Evolution (LTE)/LTE-Advanced (LTE-A) are used. To support mobility and smooth handoff, MIPV6 is used. To model the queries for energy requirements by the smart devices at the physical plane, an XML-based schema is used in which all the attributes with respect to energy requirements and current state of the game are included. This schema is then processed by the middleware between the cyber plane and the physical plane using some type of service oriented architecture (SOA). Decisions about routing and congestion control are made at the backbone level. Once all the requests are sent to the cyber plane they are executed in the cloud-based infrastructure where an efficient virtual machine (VM) utilization is done as described in our previous papers [11, 13]. Efficient utilization of VMs is important because it increases the overall throughput and performance of the proposed coalition game. In the proposed coalition game, the execution of various jobs is done in paralllel with VM migration to increase the overall throughput of the system.

Performance Evaluation

Simulation Settings

To evaluate the proposed coalition game, a cyber-physical system was developed with a finite number of devices as the players that interact with the cloud-based control center. More than 1000 traces of the movements of PHEVs are collected and analyzed with respect to the energy consumption scenario. These traces are taken as the input variable in MATLAB simulations. A cloud-based infrastructure is created with support for virtual machine migration so that under highly loaded conditions, some of the jobs can be migrated to another cloud for faster response times. Energy consumption data is retrieved from an SH for generating real traces of energy consumption patterns [14, 15]. There are 100 VMs created in the proposed solution for load management at the cloud. The following performance metrics were used in evaluating the performance of our proposed scheme:

- *Energy difference*: It is the difference between demand and supply after performing a finite number of operations with respect to energy trading.
- *Overhead generated*: It is the total number of operations performed with respect to the energy management between players and the SG.
- *Delay*: It is the total time taken by the control center to execute the requests generated from the users at the physical plane.

Figure 5a illustrates the deviation in the energy with respect to demand and supply in the proposed coalition game. As shown in the figure, with change in number of actions, the energy difference in the proposed dynamic coalition game for energy trading is reduced compared to the case with static coalition formation. This result demonstrates the effectiveness of the proposed dynamic coalition game compared to the static coalition. The main reason for such behavior is due to the adaptive nature of the players with respect to the dynamic forecasting of the demand and supply. Specifically, there is a reduction in energy consumption by 10–15 percent using the proposed coalition game.

Figure 5b shows the overhead generated with respect to the actions made by the players for demand side management. The overhead incurred is lower for the proposed coalition game compared to the static coalition game. This is due to the dynamic forecasting method used. This causes a reduction in difference between the energy demand and the energy supply at various levels in the SG CPS. Hence, there is less overhead incurred in the proposed coalition game. Specifically, the overhead incurred is reduced by more than 20 percent using the proposed coalition game.

Figure 5c shows the variation in the delay incurred in the proposed coalition game with respect to the energy trading. The proposed coalition game uses dynamic forecasting with respect to the energy availability and requirements. Consequently, intelligent decisions are made with respect to energy trading in the proposed coalition game. Hence, there is a balance between demand and supply in the proposed coalition game. The reduction in delay incurred using the proposed scheme is 10–20 percent.

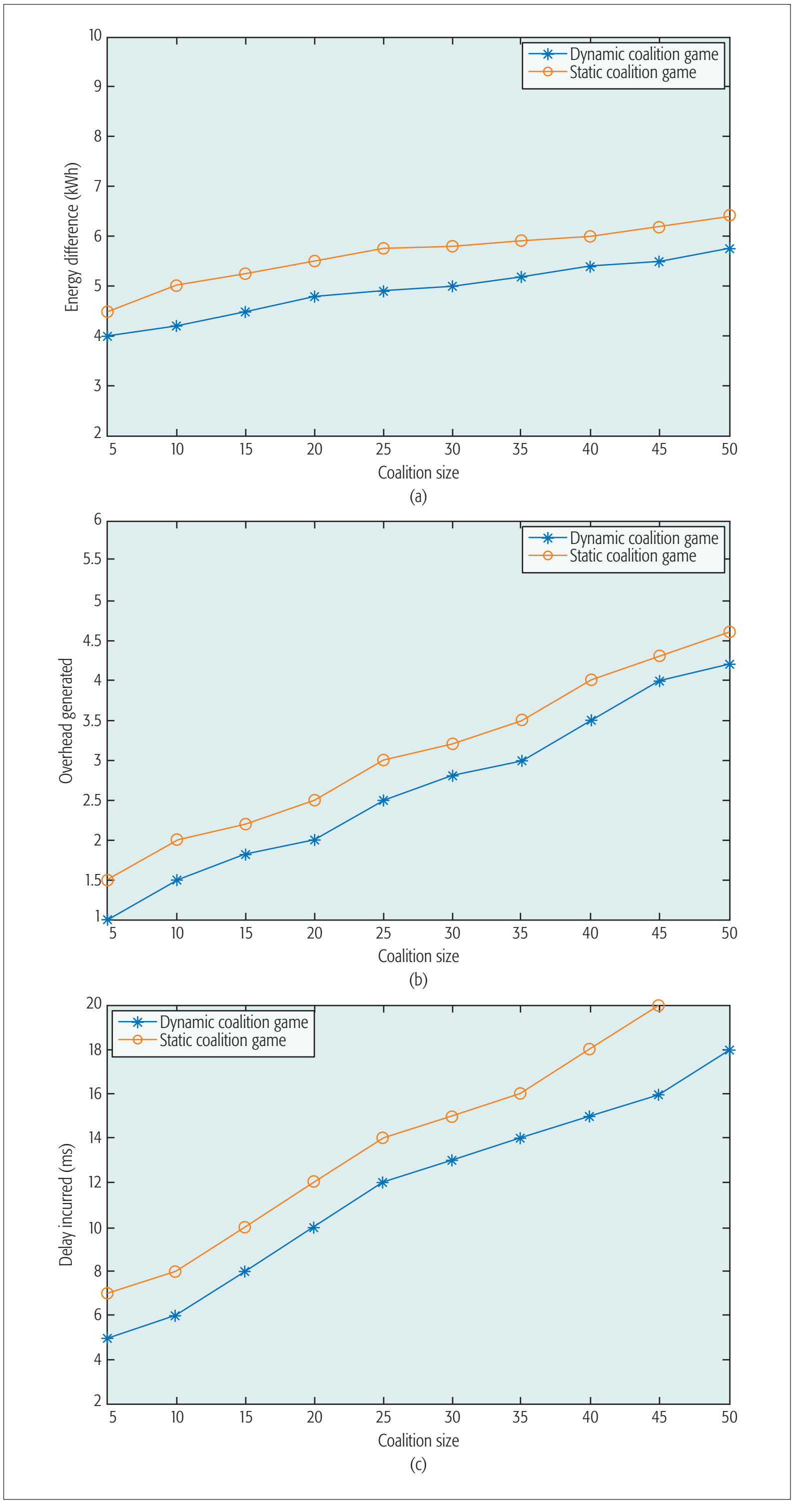

Figure 6. Variation of coalition size with: a) energy difference; b) overhead generated; c) delay incurred.

Figures 6a, 6b, and 6c show the variation of energy difference, overhead incurred, and delay with variation in the coalition size. As shown in the figure, the dynamic coalition game performs better than the static coalition game for the aforementioned performance metrics. The main reason is the adaptive moves selected by the players of the game, which enable them to make intelligent decisions with respect to charging and discharging.

As more electric vehicles appear on the market, the proposed solution can provide a cost-effective solution to end users during peak and off-peak hours for energy management. In the future, we will explore various security aspects of the proposed coalition game.

Conclusion

To satisfy the increasing demands for optimal usage of energy in various sectors, the smart grid has emerged as one of the most popular technologies aimed at minimizing the gap between demand and supply. SGs can be viewed as modern cyber-physical systems in which all the smart devices are located at the physical plane, while the control algorithms are executed in the cloud environment, which is considered as the cyber plane. The interaction between the physical plane and the cyber plane is made by constructing a backbone architecture where various types of routers and gateways are used. In this article, we propose an efficient energy management scheme in SG-based cyber-physical systems. In the proposed coalition game, all smart devices are located at the physical plane, while the cloud-based control center is assumed to be located at the cyber plane. Smart charging and discharging decisions are made in the proposed coalition game by forecasting the players' behavior using conditional entropy. Dynamic pricing and payoff variation are analyzed in the proposed game. The Nash equilibrium with respect to the incomplete information about the state of the game is also analyzed in the game. We evaluate the performance of the proposed coalition using three performance evaluation metrics, all of which demonstrate the superior performance of the proposed dynamic coalition approach. The proposed solution can be implemented in a real-world smart city environment for solving issues related to load management, frequency, and voltage fluctuations at the grid. As more electric vehicles appear on the market, the proposed solution can provide a cost-effective solution to end users during peak and off-peak hours for energy management. In the future, we will explore various security aspects of the proposed coalition game.

Acknowledgment

We thank the anonymous reviewers for their valuable suggestions and comments which helped us improve the overall content, quality, and presentation of the article.

References

[1] S. Mehar *et al.*, "Sustainable Transportation Management System for a Fleet of Electric Vehicles," *IEEE Trans. Intelligent Transportation Systems*, vol. 16, no. 3, 2015, pp. 1401–14.
[2] A. Mondal and S. Misra, " Game-Theoretic Energy Trading Network Topology Control for Electric Vehicles in Mobile Smart Grid," *IET Networks*, vol. 4, no. 4, 2015, pp. 220–28.
[3] S. Misra, S. Bera, and T. Ojha, "D2P: Distributed Dynamic Pricing Policyin Smart Grid for PHEVs Management," *IEEE Trans. Parallel and Distributed Systems*, vol. 26, no. 3, 2015, pp. 702–12.
[4] X. Fang *et al.*, "Managing Smart Grid Information in the Cloud: Opportunities, Model, and Applications," *IEEE Network*, vol. 26, no. 4, 2012, pp. 32–38.
[5] O. Tonguz, N. Wisitpongphan, and F. Bai, "DV-CAST: A Distributed Vehicular Broadcast Protocol for Vehicular Ad Hoc Networks," *IEEE Wireless Commun.*, vol. 17, no. 2, 2010, pp. 47–57.
[6] N. Kumar *et al.*, "Networks of Learning Automata: A Performance Analysis Study," *IEEE Wireless Commun.*, vol. 21, no. 6, 2014, pp. 41–47.
[7] B. J. Oommen and S. Misra, "Cybernetics and Learning Automata," *Handbook of Automation*, Shimon Nof, Ed., Springer, July 2009, Ch. 12, ISBN: 978-3-540-78830-0, pp. 219–32.
[8] B. J. Oommen and S. Misra, "A Fault-Tolerant Routing Algorithm for Mobile Ad Hoc Networks Using a Stochastic Learning-Based Weak Estimation Procedure for Non-Stationary Environments," *Proc. 2006 IEEE Int'l. Conf. Wireless and Mobile Computing, Networking and Commun.*, Montreal, Canada, June 19–21, 2006, pp. 31–37.
[9] P. B. F. Duarte *et al.*, "On the Partially Overlapped Channel Assignment on Wireless Mesh Network Backbone: A Game Theoretic Approach," *IEEE JSAC*, vol. 30, no. 1, 2012, pp. 119–27.
[10] H. Kim *et al.*, "Cloud-Based Demand Response for Smart Grid: Architecture and Distributed Algorithms," *IEEE SmartGridComm '11*, 2011, pp. 398–403.
[11] N. Kumar, J.-H. Lee, and J. P. C. Rodrigues, "Intelligent Mobile Video Surveillance System as A Bayesian Coalition Game in vehicular Sensor Networks: Learning Automata Approach," *IEEE Trans. Intelligent Transportation Systems*, vol. 16, no. 3, 2015, pp. 1149–62.
[12] S. Rusitschka, K. Eger, and C. Gerdes, "Smart Grid Data Cloud: A Model for Utilizing Cloud Computing in the Smart Grid Domain," *SmartGridComm '10*, 2010, pp. 483–88.
[13] N. Kumar *et al.*, "Performance Analysis of Bayesian Coalition Game-Based Energy-Aware Virtual Machine Migration in Vehicular Mobile Cloud," *IEEE Network*, vol. 29, no. 2, 2015, pp. 62–69.
[14] www.pjm.com/markets-and-operations/data-dictionary.aspx.
[15] A. Gelman *et al.*, *Bayesian Data Analysis*, 2nd ed., CRC Press, 2003.

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