ENTICE: Agent-Based Energy Trading with Incomplete Information in the Smart Grid

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Abstract

In this paper, energy trading for the distributed smart grid architecture is projected as an *incomplete information game* — a viewpoint that contrasts from all the existing pieces of literature available on the broader issue of energy management in smart grid. The incomplete information is considered as the real-time demand and price to grid and customers, respectively, due to the packet loss in the communication network. Therefore, the paper addresses a realistic scenario, in which real-time information to the destination may not be guaranteed to be received adequately, due to the packet loss. In the proposed scheme, we introduce two types of *intelligent* agents — *customer-agents* and *grid-agent*. The customer-agents are deployed at the customers' end, and are capable of estimating adequately the real-time price decided by the grid. On the contrary, the grid-agent is deployed at the service provider's end, and are also capable of estimating adequate real-time energy demand from the customers. Therefore, one of the key advantage of the proposed agent-based scheme is that the customers and the grid are not involved in complex calculations in order to take real-time decisions for cost-effective energy management, while there is information loss in the communication networks. In the proposed game model, the grid-agent and the customers agents are the players, and estimate real-time demand and price based on the probability of belief to each other. We show the existence of Bayesian Nash Equilibrium in the proposed model, where the utility of the players is maximized. We compare the real-time price with and without packet loss as the price with incomplete and complete information, respectively. We observe that the proposed model is beneficial for the grid, as its utility is maximized. The simulation results show that the utility of the grid increases approximately 40% over that of the existing ones under the scenario of information incompleteness.

Keywords: Smart Grid, Incomplete information, Bayesian Game, Bayesian Nash Equilibrium, Energy Management, Agent-based systems, Multi-agent

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1. Introduction

A smart grid is conceptualized as an integration of overlay communication networks with underlay electrical networks. To develop cost-effective energy supply systems, the overlay communication network plays a crucial role for energy management [1], [2]. Smart meters are implemented at the customers' end in order to communicate with the grid[1] for real-time price [3], [4]. Consequently, the customers optimize their energy consumption profile according to the price information received from the grid. Similarly, the grid receives real-time energy demand from the customers with the help of bi-directional communication facility. Thus, the grid estimates the real-time demand. Accordingly, energy is supplied by the grid (generators) to the customers in order to fulfill their requirements, and so as to maintain supply-demand curve. Therefore, an efficient energy management scheme takes effect in a smart grid architecture. However, this energy management scheme is solely based on the real-time complete information from both ends — grid, and customers.

The deployment of wireless sensor networks (WSNs) in the smart grid is expected to be a promising approach to monitor, predict, and manage real-time energy usage in a cost-effective and efficient manner [3], [5], [6]. Erol-Kantarci et al. [7] proposed the energy management scheme for residential customers based on the real-time information generated from wireless sensor networks. However, the sensor network-based communication septems are prone to increased packet loss due to the harsh environments, resource constraints (such as energy, memory, and processing), and selfish nodes [8, 9, 10]. Therefore, the implementation of WSN for residential energy management is challenging in the smart grid. Additionally, resource over-run of any of the factors mentioned earlier may lead to packet loss in the smart grid communication networks. The selfish behavior of the sensor nodes may lead to complete information not being sent to the control center as well as to the end-users for taking adequate actions in real-time. Additionally, communication delay is also an important factor that may affect decisions taken in a time period. If the delay is greater than a certain threshold, the control center takes decisions without considering the delayed information [11]. Therefore, the delayed information is treated as lost packets. Therefore, in the communication network, the occurrence of packet loss, and information propagation delay is imminent. Consequently, the grid may not have the adequate real-time information about the customers' energy demands, and the customers may not have adequate real-time price information decided by the grid due to the packet loss in the communication network. According to Niyato et al. [12], the real-time price increases almost exponentially with an increase in packet loss in the communication networks. Thus, proper estimation

[1] In general, a service provider acts as an intermediary agent between the generators and customers. However, in this work, generator, grid, and service provider are considered as the same entity. Therefore, there is no difference among generator, grid, and service provider.

of real-time demand from customers in the presence of packet loss in the overlay communication network in the smart grid is a research challenge.

1.1. Motivation

While estimating the real-time demand and price from the customers and the grid, respectively, there is relatively a very few works which addressed the demand prediction in real-time [13]. Typical approaches for estimating real-time demand and corresponding price are based solely on the received demand and price information to the grid and customers, respectively. Consequently, relying solely on the received information may lead to mismatch between the generation capacity and the customers' requirements, while there is a packet loss in the communication networks. As a result, the grid may has to buy extra energy from the wholesale electricity market[2] at a higher price to fulfill the customers' demands, which in turn increases the real-time price of energy. Hence, the real-time price increases with an increase in the packet loss rate. Therefore, the grid serves the customers in an unreliable and cost-expensive way instead of the reliable and cost-effective ones. Similarly, the customers also fail to optimize their energy consumption cost. To the best of our knowledge, there is no such work which considers the real-time energy management problem with incomplete information, i.e., with the concentration on the packet loss in the communication networks. Therefore, the users (customers and grid) need to perform complex tasks in order to optimize the real-time energy management, while there is packet loss in the communication networks. Consequently, an adequate strategy needs to be designed which can address the issue related to packet loss in the smart grid communication networks, in order to have reliable and efficient energy supply to the customers.

1.2. Contribution

In order to address the energy management problem in the presence of packet loss in the communication networks, we introduce two types of agents in the smart grid architecture — *customer-agent*, and *grid-agent*. The customer-agent is deployed at the customer's end, which is autonomously capable of predicting adequate real-time price decided by the grid. On the other hand, the grid agent is deployed at the service provider's end, and predicts the real-time demand from the customers in adequate manner. One of the key advantage of using the agent-based approach is that the customers and grid do not need to bother about the packet loss in the communication networks. The *agents act intelligently* in order to handle the incompleteness of real-time information.

[2]In a smart grid, typically, the micro-grids distribute electricity to the customers as a combination of renewable and non-renewable energy. Additionally, the micro-grids have self-generated energy sources. Therefore, firstly, the micro-grids provide services to their customers with the self-generated energy, and secondly, the rest of the required energy to fulfill the customers' demands, can be bought from the main grid which is known as wholesale electricity market. Therefore, the wholesale electricity market is a common platform for all the service providers from they are allowed to buy electricity through the bidding process.

Furthermore, the customer-agents have the ability to predict the adequate real-time price information, and take optimal decisions depending on their owners' preferences. Similarly, grid-agent also has the capability to predict the adequate energy demand from the customers, and decides real-time price for maximizing the profit. Therefore, both the agents act autonomously in order to maintain the energy supply-demand curve.

With this, in this paper, we propose a real-time energy management scheme in smart grid with *incomplete* information, named as *ENTICE* — *Energy Trading with Incomplete Information* — specifically, in the presence of packet loss due to the communication constraints mentioned earlier. We design the real-time energy management scheme with incomplete information as a *Bayesian game*. In such a game model, the grid-agent acts as one player, and the customer-agents act as other players. The customer-agent take real-time decision on energy consumption depending on the belief strategy for the grid. On the other hand, the grid-agent decides real-time price depending on the belief strategy of the received demand from the customers. We show that *Bayesian Nash Equilibrium* exists in the proposed game model, where the utility of customers and grid is maximized, and the proposed model is well-enough to predict the real-time demand and price to the grid and the customers, respectively. In brief, our contributions in this work are as follows.

- We model energy trading in smart grid as an incomplete information game, due to the presence of packet loss in the associated communication network. In such a game model, two types of agents — customer-agent and grid-agent — are used which can intelligently estimate the real-time price and demand, respectively. The customer-agents are deployed at the customers' end, and the grid-agent is deployed at the service provider's end. Therefore, the customers and grid are not involved in the complex calculations, while there is a packet loss in the communication networks.

- We propose a real-time energy management policy, which is based on the probability of belief strategy for the customers' demands to the grid-agent, to counter the information incompleteness. On the other hand, the customer-agents take optimal decisions for cost-effective energy consumption based on belief strategy of the real-time price decided by the grid.

- Consequently, we present algorithms for the grid-agent and the customer-agents by following Bayesian Nash Equilibrium for maximizing the utility for both ends — grid, and customers.

- We evaluate the proposed scheme and show that the agent-based energy management scheme outperforms than the existing ones, while there is packet loss in the communication networks. The simulation results show that the customers' utility increases on an average 40% than the existing ones by considering the incompleteness of the real-time information.

1.3. Organization

The rest of the paper is organized as follows. In Section 2, we briefly present the literature review for energy management based on information. Section 3 describes the system model related to the problem. We propose the solution of the problem in Section 4. For the solution of the problem, a Bayesian game with incomplete information is formulated. In Section 5, we present the results of performance evaluation of the proposed solution approach. Finally, in Section 6, we summarize our proposed approach with some future extensions.

2. Related Works

Several issues related to communication-based energy management in smart grid are addressed in the current state-of-the-art of the smart grid systems [14], [15], [16], [7], [12], [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [22], [31], [32]. Some of the existing literature are discussed in this Section. Niyato et al. [12] described the impacts of packet loss in smart grid communication architecture. They showed that with an increase in packet loss rate, the real-time price increases proportionately. To establish the communication architecture, they used data aggregator unit (DAU), and meter data management systems (MDMS). A DAU sends real-time data generated from smart meter to the MDMS for energy management, and accordingly, the service provider takes necessary decision. They used a queuing model to quantify packet loss due to congestion at the DAU.

Misra et al. [31] studied the impact of self-generated energy at the customers' end, and showed that the customers can significantly reduce the energy consumption cost. Rad et al. [16] discussed a distributed energy management scheme as a scheduling game for autonomous demand side management. In such a game model, the authors assumed that the customers can adopt adequate pricing tariffs, and accordingly, they consume energy in timely manner to reduce the electricity bill. However, due to the incomplete information to the customers, they may not be able to adopt adequate pricing tariffs. Similar to this, Liang et al. [18] also studied a power scheduling scheme based on quality of energy (QoE) in the smart grid to reduce the consumption cost. On the other hand, wireless sensor networks are used for real-time energy management for cost-effective energy supply [7]. The sensors are deployed at the customers' end to communicate with the smart meters, and according to real-time price information, the appliances are scheduled automatically.

In [19], the authors discussed the communication architecture required to support smart grid. They introduced a mesh network architecture, referred to as local wireless mesh network (LWMN), with the combination of home area networks (HAN), neighborhood area networks (NAN), and local electrical equipment. They used smart relay systems to send data from smart meter to the service provider. The authors claimed that this relay device is selected optimally to send real-time data. In [20], the authors also introduced a scheme for cooperative transmission of meter data to the utility provider. After receiving the data from DAU, the MDMS estimates the supply-demand curve, and optimizes the real-time price to maximize grid's utility. In their proposed approach, they formulated a non-cooperative game model to analyze the relay transmission from the smart meter, and also established the Nash Equilibrium strategy. The authors claimed that their proposed approach is useful in establishing reliable wireless network for the smart grid architecture.

Soliman et al. [27] proposed an optimal power management scheme for residential customers in the smart grid. The authors discussed the process of minimizing the electricity cost to the customers with real-time price information. They showed that energy storage and local distributed generation can facilitate cost effective energy supply to the customers. However, the scheme is fully dependent on the real-time information (such as demand and price) to the grid and customers. Therefore, the implementation of storage devices and local generation may not be fruitful without adequate real-time information. The feasibility of smart grid communication architecture was studied in [17]. The requirements to establish the architecture was also studied by the authors. They proposed two types of prioritized events operation — *high*, and *low*. The information treated as *high priority* correspond to emergency events to be sent to the control center. The *low priority* information is for asset management tasks. They also proposed a three-layer architecture to have reliable smart grid communication. The first layer architecture is a cluster of wireless sensor nodes and master nodes. The second and third layers are for communication between the master nodes and the adjacent clusters, and between the master nodes and the control center, respectively.

In [15], the authors proposed time of use (TOU) aware energy management system. For example, as during peak-hours of a day, the price is high, they suggested energy consumption during non-peak hours. However, without proper communication mechanism, this method may not work well. In [14], the authors proposed an OFDMA-based communication model for smart grid energy management. In this model, the smart meters are connected to the central communication model, and the control center can access the smart meter data simultaneously. A game theoretic coalition formation approach is presented by Wei et al. [22] to reduce power loss in the electrical network. Micro-grids can expand and shrink their service region depending on the supply and demand to the grid. Micro-grids exchange energy with one another, rather than transmitting to the macro-station. In such a scenario, the coalition formation among the micro-grids depend on the real-time information available to them. Therefore, the communication network plays an important role to establish reliable and cost-effective energy supply to the customers. A real-time digital system for condition monitoring in smart grid is proposed in [25]. The digital system based on hybrid network architecture (HNA) with the integration of wired, wireless, power line communication, and controller area network (CAN). The performance of the proposed scenario is evaluated in underground electric substation. The proposed network architecture facilitates the smart grid for cost-effective energy supply.

Although different technologies are proposed to facilitate the smart grid requirements, the analysis of the existing literature reveals that *energy management decisions in smart grid in the presence of packet loss are unreliable*. Specifically, packet loss in communication systems makes it difficult to estimate proper demands from the end users. Therefore, in this paper, we propose an approach for energy trading in smart grid in the presence of packet loss, i.e., with *incomplete information* from both sides — grid, and customers.

3. System Model

Figure 1 shows the communication architecture and energy consumption process of the customers in a smart grid. Let there be N customers, where $N \in \mathbb{N}$. The smart meters, which are deployed at the customers' end, are connected with customer-agents for estimating real-time price decided by the grid. I a similar way, the customer-agents communicate with the service provider with the help of DAUs for the required energy, $x_{i,t}$, for customer $i \in [1, N]$, at time $t \in T$, where T is the set of different time periods of a day. Therefore, the customer-agents act as a middleman between the smart meters and the DAUs in order to provide adequate real-time price to the smart meters. The DAU sends the customers' data to the meter data management system (MDMS) in order to have total demand from the customers, $\mathcal{X}_t$ at the time t. Similar to the customer-agents, the grid-agent is deployed at the service provider's end to estimate the adequate real-time energy demand. After estimating the adequate demand, the grid-agent sends the real-time demand to the service provider. Eventually, the service provider also communicates with the generation unit (which may be renewable or non-renewable) to estimate the real-time supply, $\mathcal{W}_t$, at the same time for reliable energy services to the customers. According to the received information about the real-time supply, $\mathcal{W}_t$, and the demand, $\mathcal{X}_t$, the grid decides the real-time price, p_t, and sends the price to the customers for cost-effective energy supply.

3.1. Role of Customer and Grid Agents

In a smart grid architecture, we consider that a single grid provides energy to multiple customers. In such a scenario, two types of agents are considered — customer-agents and grid-agent. The customer-agents deployed at the customers' end are responsible for providing cost-effective energy consumption using different mechanisms such as demand scheduling [33]. On the other hand, the grid-agent deployed at service provider's end is responsible for maintaining balance between real-time energy supply and demand in order to provide reliable energy service to the customers. Therefore, in brief, the customer-agents and grid-agent are two different entities in terms of *architecture*, *capabilities*, *resource requirements*, and *efficiency*, which are discussed above.

As discussed in Section 1, due to the packet loss in the smart grid communication networks, real-time energy price and demand received by the customer-agents and the grid-agent, respectively, are not the actual ones. Therefore, in addition to the above mentioned responsibilities, the customer-agents and

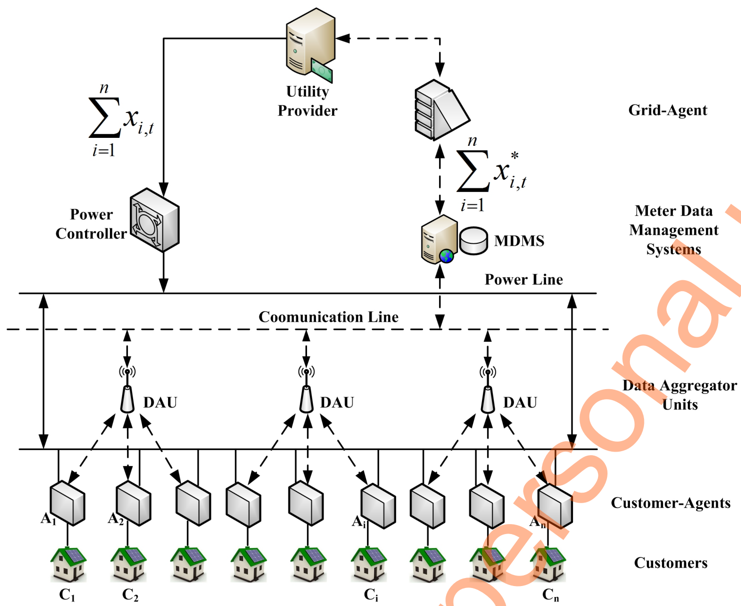

Figure 1: A distributed communication architecture in a smart grid

grid-agent need to estimate real-time energy price and demand, respectively. Consequently, in this paper, we propose an energy management scheme in the presence of customer-agents and grid-agent, while there is a packet loss in the smart grid communication networks (refer to Section 4).

3.2. Energy Consumption Profile

The set of customers is represented as a set $\mathcal{N} = \{1, 2, ..., N\}$. The customers consume energy according to their requirements. Therefore, let the demand for each customer in a day be denoted as $x_{i,req}$, where $i \in [1, N]$[3]. So, the energy demand for a customer, i, during a time period, t, can be expressed in vector form as follows: $x_{i,t} = \{x_{1,t}, x_{2,t}, ..., x_{N,t}\}$ where $i \in [1, N]$. Therefore, the grid-agent receives real-time total energy demand, $\mathcal{X}_t$, from the customers for the t^{th} time period, while there is no information loss in the communication networks. On the other hand, due to the information loss in the communication network, the grid receives real-time total energy demand, $\mathcal{X}_t^*$, from the customers. Therefore, the received demand to the grid with and without packet

[3]In a practical scenario, different customers may have different energy requirements. Therefore, though the energy requirements for different customers are different, the grid estimates the real-time demand depending on the total demand received from the customers in a particular time-slot. Therefore, in the proposed scheme, we consider different energy requirement for each customer, and we estimate the real-time demand depending on the total demand received from the customers as the grid needs to deal with total energy demand and supply.

loss is represented mathematically as follows:

$$\mathcal{X}_t = \sum_{i=1}^{N} x_{i,t} \quad \text{and} \quad \mathcal{X}_t^* = \sum_{i=1}^{N} x_{i,t}^* \tag{1}$$

In the smart grid architecture, the grid always takes decisions based on the total demand from the customers instead of the individual ones [34]. Therefore, in general, the grid-agent is unable to distinguish the different received demand information from the customers. Consequently, in the proposed scheme, the grid-agent takes decisions based on the total received demand from the customers.

3.3. Pricing Policy Based on Information

The objective of the grid is to maximize its utility while considering customers' participation. Therefore, the grid decides the real-time price as p_t to maximize its utility, while considering that the energy supply cost is time-invariant. On the other hand, the customers consume energy based on the real-time price. Therefore, the corresponding optimization problem with the supply and demand attributes is as follows.

$$\text{Maximize} \sum_{t=1}^{T} \mathcal{X}_t p_t - \Big(\sum_{r=1}^{k} \mathcal{W}_{r,t} c_{r,t} + \sum_{\tilde{r}=1}^{m} \mathcal{W}_{\tilde{r},t} c_{\tilde{r},t} \Big)$$

subject to

$$\sum_{i=1}^{N} x_{i,t} \leq \Big(\sum_{r=1}^{k} \mathcal{W}_{r,t} + \sum_{\tilde{r}=1}^{m} \mathcal{W}_{\tilde{r},t} \Big), \tag{2}$$

$$\mathcal{X}_t \geq 0 \tag{3}$$

where k and m are the number of renewable and non-renewable energy sources, respectively. $c_{r,t}$ and $c_{\tilde{r},t}$ denote the cost for renewable and non-renewable energy supply, and p_t is considered as a quadratic cost function with the total energy demand, i.e., $p_t = \alpha \mathcal{X}_t^2 + \beta \mathcal{X}_t + \gamma$, where α, β, and γ are predefined constants. Equation (2) ensures that the total demand, $\mathcal{X}_t$, should be always less than or equal to the total supply, $\mathcal{W}_t$, to maintain the supply-demand curve, in order to have reliable energy supply to the customers in every time periods. $\mathcal{W}_t$ is considered as a combination of renewable, $\mathcal{W}_{r,t}$, and non-renewable, $\mathcal{W}_{\tilde{r},t}$, energy supply. The total demand is always positive and real, and is denoted in Equation (3).

Similarly, customers also try to optimize the energy consumption based on the real-time price to minimize the energy consumption cost. The optimization problem for a customer can be represented as follows.

$$\text{Minimize} \sum_{t=1}^{T} x_{i,t} p_t, \ \text{where } i \in [1, N]$$

subject to

$$x_{i,req} \leq \sum_{t=1}^{T} x_{i,t}, \ \text{where } i \in [1, N] \tag{4}$$

where $x_{i,req}$ is the required energy of customer i in a day. Equation (4) represents that the total energy expenses, $\sum_{t=1}^{T} x_{i,t}$, during a day must be greater than or equal to the required energy, $x_{i,req}$, for the day of the customer $i \in [1, N]$.

3.4. Impact of Packet Loss

Due to packet loss in the communication system, real-time energy demand estimation is challenging to the grid, and, thus, inefficient energy supply may take place. In this situation, the cost of energy increases almost exponentially with an increase in the packet loss rate (than that of without packet loss). Let the energy demand from a customer be bounded by $[0, \mathcal{D}_{max}]$, where $\mathcal{D}_{max}$ is the maximum demand of a customer. The probability of real-time demand of a customer, i, $i \in [1, N]$, with packet loss, can be represented as follows [12].

$$\tilde{\pi}_{\omega,i} = \begin{cases} \pi_{\omega,i} + \mathcal{L}_i(\sum_{\omega' \in \Omega \setminus \{0\}} \pi_{\omega',i}) & \text{if } \omega = 0; \\ (1 - \mathcal{L}_i)\pi_{\omega,i} & \text{if } \omega > 0. \end{cases} \tag{5}$$

where, $\pi_{\omega,i}$ denotes the probability of scenario ω of the customer i, $i \in \mathcal{N}$, which is estimated without packet loss. The scenario space Ω is defined as: $\Omega = \{0, 1, ..., \mathcal{D}_{max}\}$. $\mathcal{L}_i$ denotes the packet loss rate of customer i. Interested readers can find further insight of this in [12].

3.5. Use of Bayesian Game Theory

In a real-life scenario, a player (decision maker) has partial information about other players. Therefore, assuming that a player has complete information about other players is a strong assumption, particularly in the presence of any information loss. In Bayesian game theory [35], one player can estimate the probability of belief strategies about other players. Consequently, after estimating the probability of belief strategy about a player, we can have a scenario with complete information, in the presence of information loss in the system. Bayesian game based approach where one player has incomplete information about other players. In contrast to the Bayesian game, other game theories can be used while all the players have complete information about other players.

In the proposed scheme, we have two players — customer-agents and grid-agent. The customer-agents control the energy consumption at the customers' end. On the other hand, the grid-agent controls the balance between real-time energy supply and demand. However, due to the packet loss in the smart grid communication network, the received information is incomplete at the customers' side and as well as the grid side. Therefore, the customer-agents and grid-agent need to estimate real-time price and demand for cost-effective and reliable energy service, respectively, when there is packet loss in the smart grid communication networks. Consequently, real-time energy demand can be treated as *incomplete* information for the grid. As a result, the energy management scheme in a smart grid architecture is to be considered as an optimization model with *incomplete* information. As discussed above, the Bayesian game can be used to deal with such incomplete information in the smart grid. Therefore, we use Bayesian game theory framework, which is suitable for addressing the incompleteness of the real-time information [35], where single utility provider services multiple customers. In Section 4, we discuss the energy management scheme with incomplete information as a Bayesian game.

4. Solution Approach

4.1. Game Formulation

To study energy management under incomplete information in a smart grid, we use the static Bayesian game with incomplete information [35]. In the proposed scheme, the grid-agent acts as one player, and customer-agents act as other players of the game. According to the Section 3, there are N customer-agents who consume energy from the grid, and there be M players as a combination of grid-agent and customer-agents. Therefore, $M = N + 1$, as only one grid-agent is considered in this work. The static Bayesian game, $\mathcal{G}$, with finite number of players, is defined in the strategic form as:

$$\mathcal{G} = \Big\{\mathcal{M}, \mathcal{T}, \mathcal{A}_g, \mathcal{A}_c, \{\theta_i\}_{i\in\mathcal{M}}, \{p_i\}_{i\in\mathcal{M}}, \{\mathcal{U}_i\}_{i\in\mathcal{M}}\Big\}$$

The components of the game with incomplete information are as follows:

- A set of players: $\mathcal{M} = \{g, c_1, c_2, ..., c_N\}$, where g denotes the grid-agent which acts as Player 1, and the customer-agents are denoted as $c_1, c_2, ..., c_N$, which act as Players 2.
- The set of states of nature: $\mathcal{T} = \{t_1, t_2, t_3\}$, where t_1 denotes on-peak hour, and t_2, t_3 denote mid-peak and off-peak hour, respectively.
- The set of actions for the grid-agent is $\mathcal{A}_g$, where $\mathcal{A}_g \in \{p_h, p_m, p_l\}$. p_h, p_m and p_l denote the high, mid or low nature of real-time price, respectively. The set of actions of a customer-agents is represented as $\mathcal{A}_c$, where $\mathcal{A}_c \in \{E_c, \bar{E}_c\}$, where E_c denotes that the customer consumes energy, and $\bar{E}_c$ denotes that the customer does not do so.
- A set of types of the player, i: θ_i, where $i \in \{g, c\}$. The type set for Player 1 (i.e. grid-agent) is denoted as $\theta_g = \{\mathcal{D}_h, \mathcal{D}_m, \mathcal{D}_l\}$, where $\mathcal{D}_h$

denotes that the *demand is high*, and $\mathcal{D}_m$ and $\mathcal{D}_l$ denote that the *demand is moderate* and *low*, respectively. The type set for Player 2 (i.e. customer-agents) is denoted as $\theta_c = \{d_c\}$, where d_c denotes the energy demand of the customer. All the types of players are denoted as set Θ, i.e., $\theta_i \in \Theta$.

- A probability function, $p_i : \theta_i \to \Delta(\theta_{-i})$ for player i (g or c), specifying the belief about the type of player $-i$ (c or g).
- A payoff function for the players. We denote the utility for grid (evaluated by grid-agent) as $\mathcal{U}_g : \mathcal{A}_g \times \theta_g \to \mathbb{R}$, and utility for customer (evaluated by customer-agent) as $\mathcal{U}_c : \mathcal{A}_c \times \theta_c \to \mathbb{R}$,

The types for each player may be randomly fluctuating in different time instants, as demand from the customers is different at different instants. Hence, we assume that the type, θ, is randomly distributed according to a distribution function $\mathcal{F}_i(\theta_i)$, where the density function $f_i(\theta)$ is positive in the whole interval $[\theta_{-i}, \theta_i]$. In practical network scenario, the exact realization of the game for grid is typically known only to it. Similarly, the type of customer is typically known only to the customer [36]. Thus, the types, θ_i, for a player, i, are private information of the grid (or the customer) to the customer-agents (or the grid-agent).

Let the set of possible strategies for the players be $\mathcal{S}$. Then Player 1, i.e., grid-agent's set of possible strategies, $\mathcal{S}_g$, is the set of all possible functions with domain θ_g, and action $\mathcal{A}_g$. In other words, $\mathcal{S}_g$ is a collection of functions $\mathcal{S}_g : \theta_g \to \mathcal{A}_g$. Similarly, Player 2, i.e., customer-agents' possible strategies, $\mathcal{S}_c$, is a collection of functions $\mathcal{S}_c : \theta_c \to \mathcal{A}_c$. In such a strategic condition, all the players know their utility function. Equivalently, it can be said that they know their own types, θ_g (or θ_c). Now, Player 1 (or 2) may be uncertain about Player $2's$ (or $1's$) utility function. Thus, $p_g(\theta_c|\theta_g)$ denotes the probability of Player $1's$ belief about Player $2's$ type being θ_c. According to the Bayes rule, probability of the belief strategy for Player 1 can be expressed as follows:

$$p_g(\theta_c|\theta_g) = \frac{p(\theta_g, \theta_c)}{p(\theta_g)} = \frac{p(\theta_c, \theta_g)}{\sum\limits_{\theta_g \in \Theta} p(\theta_c, \theta_g)} \tag{6}$$

4.2. Real-time Pricing with Complete Information

In the complete information game, the grid-agent and the customer-agents know all the types of each other. The type can be represented in a vector form as $\theta = \{\theta_g, \theta_c\}$, and is known to the grid-agent and the customer-agents. Then, the distribution function in Section 4.1 is either 1 or 0, i.e., $\mathcal{F}_i(x) = 0$ for $x < \theta_i$, and $\mathcal{F}_i(x) = 1$ for $x \geq \theta_i$, where θ_i is the realization of the player's type, and $i \in \{g, c\}$. In the game with complete information, general Nash Equilibrium exists [37], and, thus, we limit our discussion in the game with complete information.

Definition 1. *The Nash Equilibrium in a complete information game is a strategy profile with each player's best response to the strategies of other players [37].*

4.3. Real-time Pricing with Incomplete Information

In the game with incomplete information, the grid-agent cannot observe the type, θ_c, of the customer-agents. Hence, the aim of the grid is to maximize its own revenue, while taking customers' participation into account. In this situation, energy transfer depends on the types of the players. We consider that the cost function is quadratic with real-time demand, as mentioned in Section 3.3. So, the price, p_t, per unit energy depends on the type, θ_i, of the players. Let $\sigma_i \triangleq p_t^{-1}$ be the inverse function of p_t such that $\theta_i = \sigma_i(p_t(\theta_i))$. We also assume that the distribution function, $f_i(\theta_i)$, is positive-valued over (θ_g, θ_c), as discussed earlier.

In the game with incomplete information, if we design the outcome of the game, $\mathcal{G}$, as $x_g(v_g)$ for the grid-agent, and the cost function as $\mathcal{C}_g(\theta_i, v_g)$, $i \in g$, then the utility function for the grid can be expressed as follows:

$$\mathcal{U}_g(v_g) = v_g x_g(v_g) - \mathcal{C}_g(\theta_i, v_g), \qquad \text{where } v_g \in \{p_t\} \tag{7}$$

and

$$\begin{aligned} x_g(v_g) &= Pr[x_g(v_g) = 1|v_g] \\ &= E[x_g(v)|v_g] \\ \mathcal{C}_g(\theta_i, v_g) &= E[\mathcal{C}_g(\theta, v)|v_g] \end{aligned}$$

The grid-agent estimates the demand depending on the belief strategy for customer-agents ($p_{\theta_c|\theta_g}$). Thus, the real-time demand is estimated as follows:

$$\begin{aligned} \xi_d &= \sum_{i=1}^{\mathcal{N}} x_{i,t}^* + \sum_{i=1}^{\mathcal{N}} x_{i,t}^* \Big(1 - (p_{\theta_c|\theta_g})\Big) \\ &= \sum_{i=1}^{\mathcal{N}} x_{i,t}^* + \sum_{i=1}^{\mathcal{N}} x_{i,t}^* \Big\{1 - \frac{p(\theta_c, \theta_g)}{\sum_{\theta_c \in \Theta} p(\theta_c, \theta_g)}\Big\} \end{aligned} \tag{8}$$

Lemma 1. *The demand without packet loss is always greater than or equal to the demand with packet loss, i.e.,*

$$\mathcal{X}_t \geq \mathcal{X}_t^*$$

Proof 1. *From the general rules, due to packet loss, the receive demand decreases with the packet loss rate (ρ). Thus,*

$$x_{i,req} - \rho \frac{x_{i,t}}{100} = x_{i,t}^*$$

Let, if possible, $\mathcal{X}_t \leq \mathcal{X}_t^*$. Therefore,

$$\rho \frac{x_{i,t}}{100} = x_{i,t} - x_{i,t}^*$$

This implies that $\rho < 0$, when $x_{i,t} < x_{i,t}^*$. However, ρ cannot be negative-valued.

Thus, $\forall \rho \geq 0$, $\sum_i \sum_t x_{i,t} \geq \sum_i \sum_t x^*_{i,t}$ *or* $\mathcal{X}_t \geq \mathcal{X}^*_t$.

The real-time price is calculated according to the estimated demand by the grid,

$$p_t = \alpha \xi_d^2 + \beta \xi_d + \gamma \tag{9}$$

where α, β, γ are the predefined constants. Thus, according to Equation (7), the utility for grid is expressed as follows:

$$\mathcal{U}_g(\theta_g, \mathcal{S}(\mathcal{S}_g : \mathcal{A}_g \rightarrow \theta_g)) = \sum_{t=1}^{T} \xi_d p_t - \Big(\sum_{r=1}^{m} E_r c_r + \sum_{\tilde{r}=1}^{k} E_{\tilde{r}} c_{\tilde{r}} \Big) \tag{10}$$

and, the utility for customer is as follows:

$$\mathcal{U}_c(\theta_c, \mathcal{S}(\mathcal{S}_c : \mathcal{A}_c \rightarrow \theta_c)) = \sum_{t=1}^{T} x_i p_t - \sum_{t=1}^{T} \mathcal{S}_c\big(x_i p_t\big), \ \forall i \in [1, N] \tag{11}$$

Definition 2. *A socially optimal allocation is the allocation of real-time price, in which total energy cost for the customers is minimized.*

Lemma 2. *In the real-time pricing game with incomplete information, if the marginal cost function* $\mathcal{C}_g(\theta_i, v_g) = \frac{\partial \mathcal{C}(\theta_i, v_g)}{\partial v_g}$ *is concave in* v_g *and* $\mathcal{C}(\max_{i \in N} \theta_i, v_g) < \infty$, *then the cost boundary function* $\Phi(\theta)$ *is represented as* $\Phi(\theta) \leq N$, *where* N *is the number of customer-agents in the game, with equality, if and only if* $\mathcal{C}(\theta_i, v_g)$ *is linear in* v_g, *and the customer-agents' types* (θ_i), $i \in [1, N]$, *are all the same.*

Proof 2. *Let* $(v_i^*)_{i=1}^N = (\varphi_i v_i)_{i=1}^N$ *be the socially optimal allocation of real-time price for a given type realization* θ, *and* $\sum_{i=1}^N \varphi_i = 1$ *and* $\varphi_i \geq 0$, $\forall\ i \in [1, N]$. *Thus, the optimal cost for the customers is represented as follows:*

$$\mathcal{C}^* = \sum_{i=1}^{\mathcal{N}} \int_0^{\varphi_i v_g} \mathcal{C}(\theta_i, v_i) dv_i \tag{12}$$

Since the cost function $\mathcal{C}(\theta_i, v_i)$ *is strictly convex in* v_i, *the marginal cost* $\mathcal{C}(\theta_i, v_i)$ *is positive for all* $v_i > 0$. *On the contrary, since* $\mathcal{C}(\theta_i, v_i)$ *is concave in* v_i, *it can be shown that* $\int_0^{\varphi_i v_g} \mathcal{C}(\theta_i, v_i) dv_i \geq \varphi_i^2 \int_0^{v_g} \mathcal{C}(\theta_i, v_i) dv_i$, *where the equality holds if and only if* $\mathcal{C}(\theta_i, v_i)$ *is linear in* v_i. *Thus, we have*

$$\mathcal{C}^* \geq \sum_{i=1}^{N} \varphi_i^2 \int_0^{v_g} \mathcal{C}(\theta_i, v_g) dv_i \tag{13}$$

Therefore,

$$\Phi(\theta) = \frac{\int_0^{v_g} \mathcal{C}(\max_{i \in N} \theta_i, v_i) dv_i}{\sum_{i=1}^N \int_0^{\varphi_i v_g} C(\theta_i, v_i) dv_i}$$

$$\leq \frac{\int_0^{v_g} \mathcal{C}(\max_{i\in N} \theta_i, v_i) dv_i}{\sum_{i=1}^{N} \varphi_i^2 \int_0^{v_g} \mathcal{C}(\theta_i, v_i) dv_i}$$

$$\leq \frac{\int_0^{v_g} \mathcal{C}(\max_{i\in N} \theta_i, v_i) dv_i}{\sum_{i=1}^{N} \varphi_i^2 \int_0^{v_g} \mathcal{C}(\max_{i\in N} \theta_i, v_i) dv_i}$$

$$\leq \frac{1}{\sum_{i=1}^{N} \varphi_i^2} \leq N$$

4.4. Bayesian Nash Equilibrium

We now evaluate the Bayesian Nash Equilibrium in the game model according to the formal equilibrium condition.

Definition 3. *Bayesian Nash Equilibrium of the game is a set of strategies, $\mathcal{S}$, where $\mathcal{S} = \{s_1, s_2, ..., s_{\mathcal{M}}\}$, satisfying two conditions as follows:*

- *For grid-agent, in every feasible strategy ($\mathcal{S}_g : \tilde{\mathcal{A}}_g \rightarrow \theta_g$), the equilibrium condition is given as:*

$$E_{\theta_c}\{\mathcal{U}_g(\theta_g, g(\mathcal{S}_g(\theta_g), \mathcal{S}_c(\theta_c)))\} \geq E_{\theta_c}\{\mathcal{U}_g(\theta_g, g(\tilde{\mathcal{S}}_g(\theta_g), \mathcal{S}_c(\theta_c)))\} \quad (14)$$

  where E is the expected value.

- *The equilibrium condition for customer-agents can be represented with the possible strategies ($\mathcal{S}_c : \tilde{\mathcal{A}}_c \rightarrow \theta_c$), as follows:*

$$E_{\theta_g}\{\mathcal{U}_c(\theta_c, g(\mathcal{S}_c(\theta_c), \mathcal{S}_g(\theta_g)))\} \geq E_{\theta_g}\{\mathcal{U}_c(\theta_c, g(\tilde{\mathcal{S}}_c(\theta_c), \mathcal{S}_g(\theta_g)))\} \quad (15)$$

Theorem 1. *For Bayesian Nash Equilibrium, only mixed strategy is considered, i.e., Player 1's action is completely determined by his/her belief strategy about the other players, where the belief strategy depends on the probability distribution function $\mathcal{F}_i(\theta_i)$.*

Proof 3. *Let us consider that there exists an equilibrium point in the Bayesian game following pure strategy. Therefore, the equilibrium condition presented in Equations (14) and (15) can be represented as follows:*

$$E_{\theta_c}\{\mathcal{U}_g(\theta_g, g(\mathcal{S}_g(\theta_g), \mathcal{S}_c(\theta_c)))\} > E_{\theta_c}\{\mathcal{U}_g(\theta_g, g(\tilde{\mathcal{S}}_g(\theta_g), \mathcal{S}_c(\theta_c)))\}$$

$$E_{\theta_g}\{\mathcal{U}_c(\theta_c, g(\mathcal{S}_c(\theta_c), \mathcal{S}_g(\theta_g)))\} > E_{\theta_g}\{\mathcal{U}_c(\theta_c, g(\tilde{\mathcal{S}}_c(\theta_c), \mathcal{S}_g(\theta_g)))\}$$

However, an equilibrium point does not exist in pure strategy [35] in the Bayesian game with incomplete information. Consequently, we consider mixed strategy of the incomplete information game to have an equilibrium point of the game, and is presented in Equations (14) and (15).

Theorem 2. *For the given strategy, $\mathcal{S}$, and the distribution function, $\mathcal{F}$, in the incomplete information game, $\mathcal{G}$, the Bayesian Nash Equilibrium exists iff for all players, i,*

$$\mathcal{C}_i(\theta_i, v_i) = v_i x_i(v_i) - \int_0^{v_i} x_i(z)dz + \mathcal{C}_i(\theta_i, 0)$$

where, $i \in \{g, c\}$ and $v_i \in \{p_t, p_s\}$. p_s is satisfactory price of the customers.

Proof 4. *First, we fix v_i, and recall from Equation (7) that $\mathcal{U}_i(v_i, z) = v_i x_i(z) - \mathcal{C}_i(\theta_i, z)$. Let $\mathcal{U}_i^{'}(v_i, z)$ be the partial derivative of $\mathcal{U}_i(v_i, z)$ with respect to z, i.e.,*

$$\mathcal{U}_i^{'}(v_i, z) = \frac{\partial \mathcal{U}_i(v_i, z)}{\partial z}$$

Thus, $\mathcal{U}_i^{'}(v_i, z) = v_i x_i^{'}(v_i) - \mathcal{C}_i^{'}(\theta_i, v_i)$, where $x_i^{'}$ and $\mathcal{C}_i^{'}$ are the derivative of $x_i(\cdot)$ and $\mathcal{C}_i(\cdot)$, respectively. The game implies that $\mathcal{U}_i(v_i, z)$ is maximized at $z = v_i$. Thus, it follows that

$$\mathcal{U}_i^{'}(v_i, z) = v_i x_i^{'}(v_i) - \mathcal{C}_i^{'}(\theta_i, v_i) = 0$$

This formula must hold for all values of v_i. By substituting $z = v_i$, we get $z x_i^{'}(z) = \mathcal{C}_i^{'}(\theta_i, z) = 0$. Solving for $\mathcal{C}_i^{'}(\theta_i, z)$, and then integrating both sides of the equality from 0 to v_i, we have $\mathcal{C}_i^{'}(\theta_i, z) = z x_i^{'}(z)$. Therefore, $\int_0^{v_i} \mathcal{C}_i^{'}(\theta_i, z)dz = \int_0^{v_i} z x_i^{'}(z)dz$, which implies:

$$\begin{aligned}\mathcal{C}_i(\theta_i, v_i) - \mathcal{C}_i(\theta_i, 0) &= z x_i(z)|_0^{v_i} - \int_0^{v_i} x_i(z)dz \\ &= v_i x_i(v_i) - \int_0^{v_i} x_i(z)dz \qquad (16)\end{aligned}$$

Adding $C_i(\theta_i, 0)$ on both sides of the equality, we conclude that the equilibrium must hold.

4.5. ENTICE: The Proposed Scheme

In this section, we describe the algorithms comprising the proposed scheme, *ENTICE*. We describe the algorithm for the grid-agent and the customer-agents in Sections 1, and 2, respectively.

4.5.1. Algorithm for Grid-Agent

We show how the real-time price is decided by the grid in the presence of packet loss in Algorithm 1. The grid-agent decides the real-time price (p_t) to maximize its utility, while taking the customers' participation into account.

Algorithm 1: Algorithm for grid-agent

Input: Total supply, $\mathcal{W}_t = (\mathcal{W}_{r,t} + \mathcal{W}_{\tilde{r},t})$, Total received demand, $\mathcal{X}_t^*$, and cost for supply, $\{\mathcal{W}_{r,t}c_{r,t} + \mathcal{W}_{\tilde{r},t}c_{\tilde{r},t}\}$

Output: Real-time price, p_t

```
Observe the state of the nature, i.e., whether it is on-peak hour, off-peak
  hour, or mid-peak hour;
Estimate the type of the demand, θ_g, where θ_g ∈ {D_h, D_m, D_l};
Calculate the probability, p_g, from Equation (6);
Estimate the real-time demand, ξ_d, from Equation (8) according to p_g;
Take the action, A_g, according to the probability, p_g, of the belief;
Calculate real-time price, p_t = αξ_d^2 + βξ_d + γ;
Calculate the overall utility, U_g, according to Equation (10);
```

4.5.2. Algorithm for Customer-Agent

The algorithm for customer-agent to consume the required energy is shown in Algorithm 2. The customer consumes energy depending on the customer-agents action, demanded energy $(x_{i,t})$, and real-time price (p_t).

Algorithm 2: Algorithm for customer-agent

Input: Required energy, $x_{i,t}$, at time t

Output: Consume energy to fulfill the requirement, and maximize utility

```
Customer requests energy to the grid, x_{i,t}, at time t;
Receive the real-time price (p_t) from the grid;
Calculate the satisfactory price, p_s, based on the real-time price, p_t;
if (p_t ≤ p_s) then
    Consume energy to maximize the pay-off;
else
    Consume energy only for non-shiftable appliances;
    Wait with an waiting time, τ, until p_t ≤ p_s for shiftable appliances to
      minimize energy consumption cost;
    Consume energy after the waiting time;
Calculate the utility, U_c, according to Equation (11).
```

5. Performance Evaluation

We simulated the proposed scheme in NS-3 (http://www.nsnam.org). In Table 1, we show the different parameters used for simulation. We set the value for predefined constants in Equation (9) as: $\alpha \geq 0$, $\beta = 0$, $\gamma = 0$. In this work, the supply cost is considered as a constant value. However, the energy supply cost can also be considered as an quadratic cost function similar to the demand-cost with different values for the predefined constants α, β, and γ.

Table 1: Simulation Parameters

Parameter	Value
Number of grid	1
Number of customers	50, 100, 150, 200
Simulation area	2 km × 2 km
Demand of a customer	10-30 kWh
Energy supply	10-40 mWh
Packet loss rate	5-30 %
Cost for supply	5 Cents/kWh

5.1. Reasons for Selecting Simulation Parameters' Values

As discussed in Section 3, we consider that a single grid provides energy services to multiple customers. Additionally, different number of customers are also used to show impact on the proposed scheme, ENTICE. For simplicity, the simulation area is considered to be 2 km × 2 km. The demand of the customers is chosen between 10 kWh to 30 kWh, according to U.S. Energy Information Administration[4]. In [12], the authors considered the packet loss rate from 0 to 20%. Similarly, we consider the packet loss rate from 5% to 30%. We take the packet loss rate up to 30% to show the further effects on the energy management in smart grid. The average cost for energy supply from different sources is considered as 5 Cents/kWh (according to US DOE and the National Renewable Energy Laboratory[5]).

5.2. Performance Metrics

1. *Real-time Demand:* The actual and estimated demand are calculated without and with packet loss, respectively. The actual demand from all the customers is represented as follows: $\mathcal{X}_t = \sum_{i=1}^{N} x_{i,t}$. The estimated demand is calculated according to Equation (8). The demand with packet loss is as follows: $\mathcal{X}_t^* = \sum_{i=1}^{N} x_{i,t}^*$.
2. *Reliability of Energy Supply:* The reliability of energy supply depends on the estimated demand and actual demand from the customers. The reliability of energy supply to the customers is represented as: $\Pi = \frac{\mathcal{X}_t^*}{\mathcal{X}_t} \times 100\%$, where $\mathcal{X}_t^*$ and $\mathcal{X}_t$ denote the estimated and actual demand to the grid, respectively.
3. *Real-time Price:* The grid calculates the real-time price, depending on the received demand from all the customers, using Equation (9).
4. *Utility of Grid:* The utility of the grid is evaluated using Equation (10). The utility of the grid is calculated with actual demand, received demand, and estimated demand.

[4] `http://www.eia.gov/electricity/sales_revenue_price/xls/table5_a.xls`
[5] OpenEI Transparent Cost Database (`http://en.openei.org/apps/TCDB/`)

5.3. Benchmark

The performance of *ENTICE* is evaluated by comparing it with other schemes where the available information (with packet loss) is treated as complete information. On the other hand, *ENTICE* evaluates real-time price based on the probability of belief strategy of grid for the customers to counter the incompleteness of the available information. The assumption of availability of complete information for energy trading was made by the most of the previous authors in [16], [7]. In [16], a game theoretic energy consumption scheduling scheme is proposed. In the game model, customers' schedule their appliances based on the real-time information. A WSN-based home energy management scheme is studied in [7]. In such an energy management scheme, sensors are deployed at the customers' end, and communicate with the smart meters. We take these two literature as a benchmark to compare the proposed scheme, *ENTICE*, as both of them discussed distributed energy management scheme using real-time information. However, as mentioned before, both the literature deal with energy management while ignoring packet loss in the communication network.

5.4. Results and Discussion

5.4.1. Real-time Demand

Figure 2 depicts the real-time energy demand of the customers to the grid for three different cases — *actual demand*, *received demand*, and *estimated demand*. We notice that using the proposed scheme, the estimated energy demand by the grid closely matches the actual demand of the customers in the case of 10% packet loss rate, as shown in the Figure. Figure 2 also shows that when the packet loss rate increases to 20%, the difference between the actual demand and the estimated demand increases. However, the estimation is better than that of the received energy demand with packet loss in the communication network.

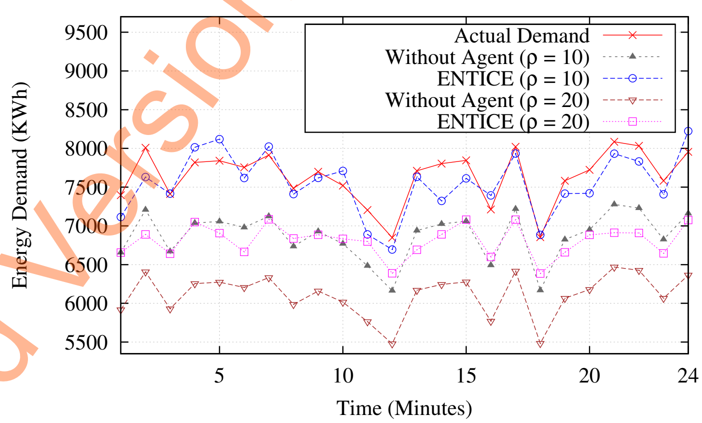

Figure 2: Real-time demand of the customers

In another experiment, we varied the number of customers from 50-200 with packet loss rate (ρ) of 10%, and the results are shown in Figure 3. *ENTICE* shows better performance than the schemes that do not consider information loss.

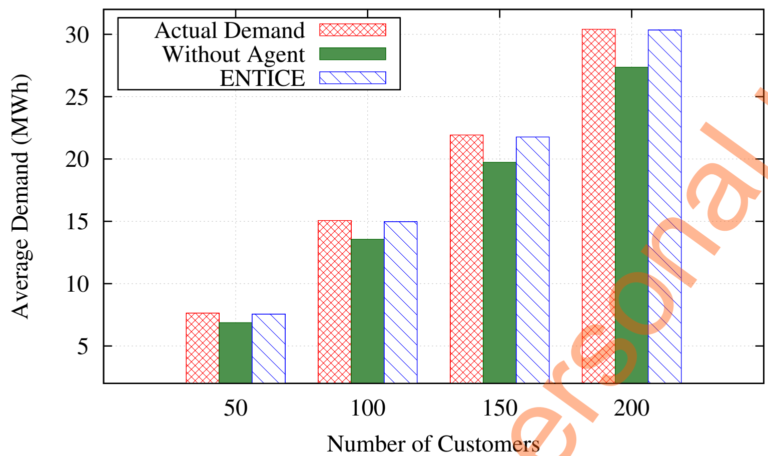

Figure 3: Demand with different customers ($\rho = 10\%$)

5.4.2. Real-time Price

We evaluate the real-time price provided by the grid according to the energy demand presented in Figure 2. For the packet loss rates of 10% and 20%, the corresponding real-time price is shown in Figure 4. We see that the difference between the actual price and the estimated price increases with an increase in the packet loss rate. However, the rate of change of this difference is moderate. On the other hand, we varied the number of customers from $50 - 200$ with packet loss rate (ρ) of 10%. The results for the corresponding real-time price are shown in Figure 5.

5.4.3. Effect of Packet Loss

The total demand from the customers is evaluated with different packet loss rates, and is shown in Figure 6. We observe that the proposed scheme exhibits significant results for estimating demand with packet loss rate up to 15%. However, when the packet loss rate exceeds 15%, the estimation of demand decreases in a moderate rate with an increase in the packet loss rate. In case of the real-time price, the estimated price has similarities with the actual price for packet loss rate up to 15%, as shown in Figure 7. Beyond this point, the value of the estimated price decreases in a reasonable manner.

5.4.4. Reliability of Energy Supply

Due to the packet loss in the communication network, grid cannot estimate adequate demand from the customers without considering the packet loss, as

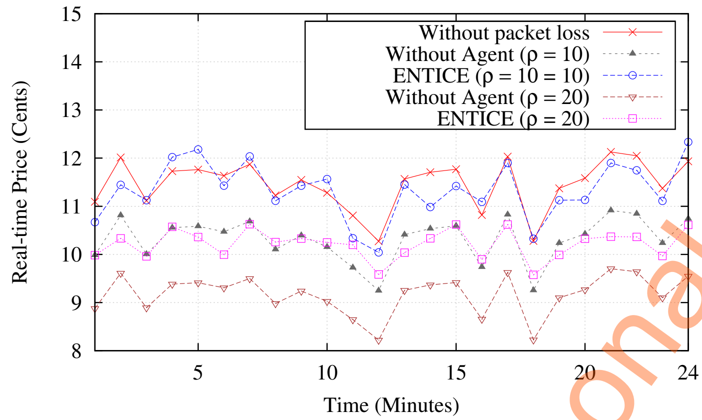

Figure 4: Real-time price decided by the grid

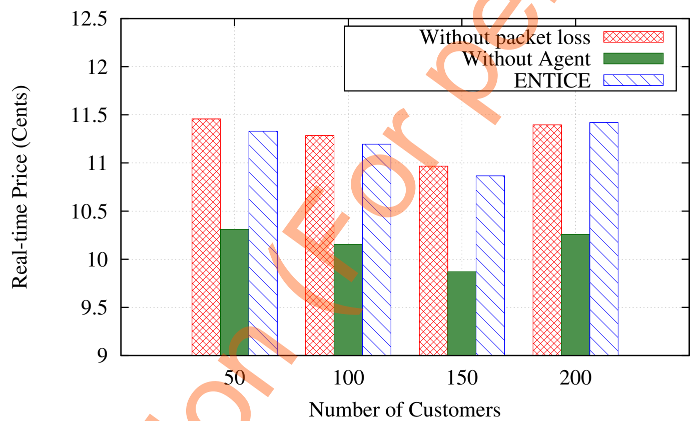

Figure 5: Price with different customers ($\rho = 10\%$)

shown in Figure 2. On the other hand, the proposed approach, *ENTICE*, estimates adequate demand from the customers. Therefore, we show the reliability of energy supply to the customers in Figure 8. We see that *ENTICE* increases the reliability of energy supply to the customers than the other schemes, which do not consider the packet loss in the communication network.

5.4.5. Utility of the Grid

We compute the utility of the grid for the proposed scheme with the actual demand to the grid. Figure 9 shows that with high packet loss rates, such as 25% and 30%, the utility of the grid is insignificant with the general communication-based schemes for smart grid. In the proposed approach, the utility of the grid remains high, and also it closely follows the actual energy demand with low

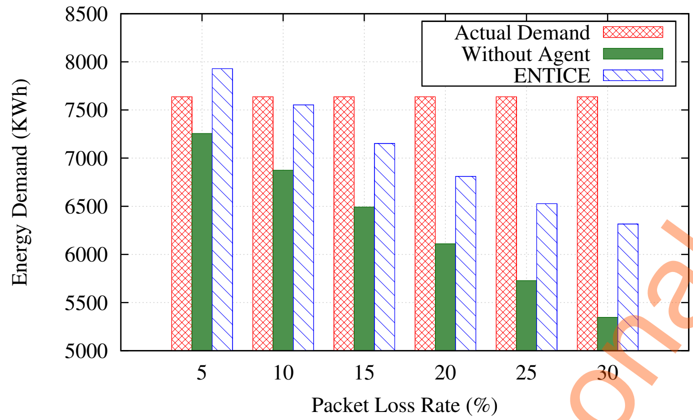

Figure 6: Demand with different packet loss rate

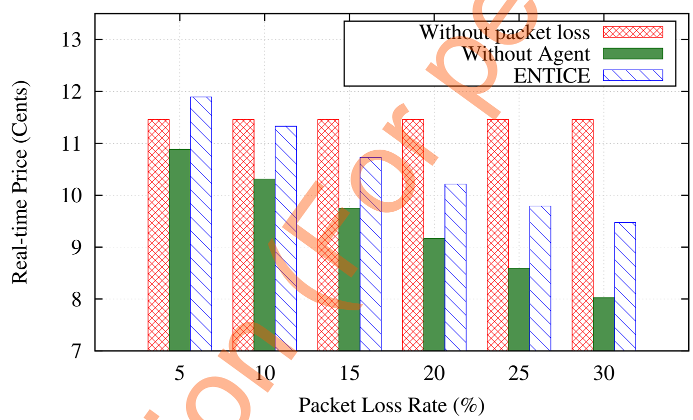

Figure 7: Price with different packet loss rate

packet loss rate. This implies that the grid maintains its profits by following the proposed scheme. Additionally, we see that the utility of the grid increases approximately 40% than that of the existing ones without considering the incomplete information scenario.

6. Conclusion

In this paper, we proposed an intelligent agent-based approach for energy trading in smart grid with incomplete information. The performance of a smart grid is affected due to packet loss in the communication network. Therefore, we analyzed the energy trading problem in smart grid as an *incomplete information* game between the grid and the customers. We introduced grid-agent

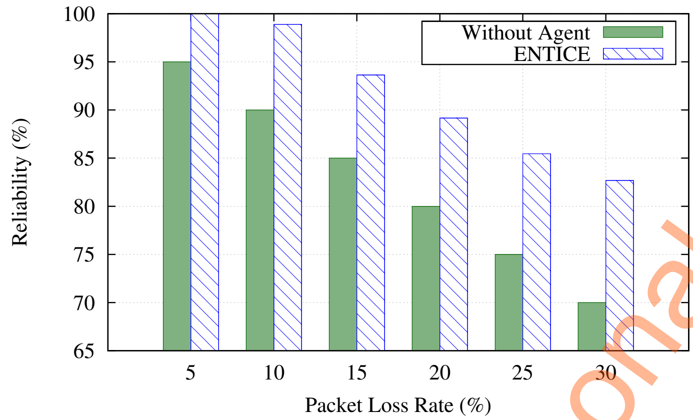

Figure 8: Reliability of energy supply to customers

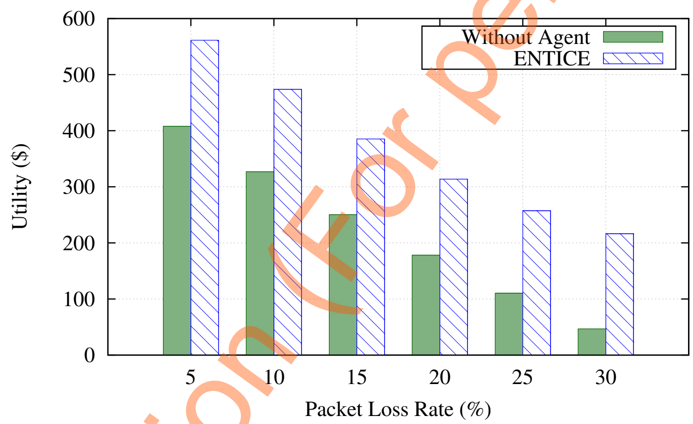

Figure 9: Utility of grid with different packet loss rate (ρ)

and customer-agents which are deployed at the service provider's end and the customers' end, respectively, in order to take optimal decisions for cost-effective energy management in the smart grid architecture in presence of information loss in the communication networks. The grid-agent estimates the real-time energy demand, depending on the probability of the belief strategy for the customers. The simulation results illustrate that our proposed scheme has significant potential to maximize the grid's revenue, while ensuring customers' participation. On an average, the utility of the grid increases approximately 40% with the estimated demand than that of the received demand with packet loss.

The future extension of this work includes the improvement of demand estimation, and designing an optimal network with this incomplete information scheme, where the packet loss rate can be minimized to have cost-effective and reliable energy service in the smart grid.

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