Dynamic Spectrum Access for Meter Data Transmission in Smart Grid: Analysis of Packet Loss

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Abstract—The smart grid uses data communications techniques to gather and transfer information for scheduling and decision making so that the electric power can be used more efficiently and economically. To reduce the cost of data communications in smart grid, in this paper, we assume that cognitive radio technique is used to transmit the meter data from smart meters to the data aggregator unit (DAU). Smart meters are deployed in the houses as the consumption nodes to measure and report a power demand. Also, smart meters are used by the generators in the community renewable power generation facility (CRPGF) which is one of the distributed energy resources (DERs), to collect and estimate a renewable power production capacity. However, the transmission of these meter data must be performed within a limited period of time (i.e., deadline). By using absorbing Markov chain, we analyze the average packet loss probability of meter data, and study the impact on the power supply cost optimization made by the meter data management system (MDMS).

Keywords—Smart grid, cognitive radio, community renewable power generation facility (CRPGF), meter data management system (MDMS).

I. INTRODUCTION

Equipped with information and communication technology (ICT), the traditional electric power grid is being improved into smart grid that emerges to be a promising direction attracting a lot of research interest recently. The smart grid can gather information of the consumer side (e.g., amount of power consumption of home appliances) and the generation side (e.g., amount of power production of distributed energy resource (DER)). As a result, smart grid can enable the consumer and the power supplier to interact in a more efficient and economical way when they make decisions on power usage and power production, respectively [1].

A typical structure of smart grid is shown in Fig. 1. At the customer side, there are houses and community renewable power generation facility (CRPGF) which uses solar photovoltaic energy system or wind turbine generators. These generators supply the renewable power to the smart grid for consumption. However, if the power consumption is more than the power production capacity from CRPGF, the additional power supply can be bought from traditional power plant. The power consumption and power production capacity data is monitored by smart meters implanted into each house and generator in the CRPGF. Smart meters will send the meter data packet about the amount of power consumption and production through data communications, specifically wireless channel, to the data aggregator unit (DAU) which subsequently forwards the data to the meter data management system (MDMS). However, the use of licensed wireless service (e.g., 3G cellular or WiMAX broadband wireless access) will incur cost to the meter data transfer for MDMS. To reduce the cost to MDMS and to increase the utilization of available wireless channels, the cognitive radio becomes a potential alternative for meter data transfer. In this paper, we consider the use of cognitive radio for transmitting meter data packets from the smart meters in a service area to the DAU. With cognitive radio, the smart meters act as secondary users and perform dynamic spectrum access (DSA) to use the licensed channels which belong to their licensed users (i.e., primary users), and vacate the channels when the primary users want to use them.

The amount of renewable power produced by the CRPGF will be affected by the weather intensively. For example, if the weather changes from sunny to cloudy, the expected amount of power produced by solar photovoltaic energy system will dramatically decrease. And if the wind speed decreases, the expected amount of power produced by the wind turbine generators will also decrease. Since the weather usually changes abruptly, it will leave the smart meters only limited period of time to transmit their data to the DAU before the deadline of cost optimization made at the MDMS. Moreover, due to the intermittent availability of primary channels and transmission error, the packet loss is inevitable.

The MDMS gathers all the data from consumers and CRPGF, and then optimizes the cost of power supply (i.e., to buy power from traditional power plant). However, since the power demand and production from consumer and generator in CRPGF, respectively, are unpredictable and change over time, the operation decision of power system is made in two stages [2]. At the first stage which is called unit commitment, the utility company with MDMS reserves power supply from power plants according to the expected power demand and production from CRPGF. Then, at the secondary stage which is called economic dispatch, if the
amount of reserved power together with the amount of produced renewable power from the CRPGF cannot meet the actual power demand, the rest amount of power demand will be bought from power plant. Since the power reserved at the first stage is made in advance before actual amount of power demand reveals, the utility company can choose and buy power with a forward price cheaper than that bought at the second stage with an option price. The packet loss from data communication to transfer meter data from consumer and CRPGF will affect the accuracy and optimality of the decision made by MDMS, and hence, the cost paid by the customers.

Compared with [3] in which the packet congestion at the DAU was studied, we consider the packet loss in the transmission from smart meters to DAU. Specifically, by applying absorbing Markov chain, we obtain the packet loss due to the transmission based on dynamic spectrum access given the time constraint. That is, the meter data has to be collected and sent to DAU before the deadline. Then, the effect of this packet loss to the cost optimization of MDMS is considered for both consumer and CRPGF sides. The cognitive radio was firstly proposed to be tied with smart grid in [4]. In [5], the cognitive radio was proposed as communication tool for wide area network (WAN) in the smart grid and its performance on coverage area was discussed. However, none of these works considered the meter data transmission with deadline and CRPGF. Besides, in our work, we obtain the average packet loss probability for neighborhood area network (NAN) (i.e., the network connecting smart meters and the DAU) which implements cognitive radio as transmission technique in our model and study the impact of packet loss probability on the cost optimization.

The rest of this paper is organized as follows. The system model and assumptions are described in Section II. Section III discusses the absorbing Markov chain to model the packet transmission of nodes, and explains the procedure from which we obtain the average packet loss probability. The cost optimization and the effect of packet loss probability are discussed in Section IV. Section V provides the description of performance evaluation and results. Section VI gives a conclusion.

II. SYSTEM MODEL AND ASSUMPTIONS

In Fig. 1, the smart meters are implanted into each house and generator in CRPGF to measure the power demand from house or power production capacity from generator in CRPGF. Then, the smart meters transmit the packets containing the estimated power consumption and production to the DAU. DAU forwards this meter data to the MDMS for power supply cost optimization. The smart meters use cognitive radio to transmit meter data packet on the channels when the channels are not occupied by the primary users. Therefore, smart meters are considered to be the secondary users in this case. We assume that the buffer size in the DAU is large enough and the transmission rate of the DAU is sufficiently fast such that there is no packet dropped at the DAU.

The constraints here on the packet transmission from secondary users to the DAU include that the meter data must be transferred to DAU within a limited period of time. This is due to the fact that the estimation of power consumption and production must be done in a timely manner to achieve the accuracy. The cost optimization will be made at the MDMS for one or two times per hour. However the weather condition usually changes abruptly and the weather condition will affect the expected amount of renewable power produced by CRPFG. Once the weather changes or the power demand from the customers changes, the updated meter data should be transmitted to the MDMS immediately before the deadline of the cost optimization. In this case, if the packet cannot be transmitted before the deadline, the meter data in this packet is considered to be obsolete and the packet will be discarded. Besides, we assume that there exists packet transmission error and contention among several secondary users for the same primary channel.

A. Channel Characteristics

The transmissions of primary users and secondary users are time-slotted, and it is assumed that at most one packet can be transmitted in one time slot. In each time slot, a primary channel can be either available for a secondary user or occupied by a primary user. The state of primary channel $l$ is modeled as a two-state (i.e., idle or occupied) discrete-time Markov chain. The transition matrix for this Markov chain can be expressed as follows:

$$C_l = \begin{bmatrix} C_{0,0}(l) & C_{0,1}(l) \\ C_{1,0}(l) & C_{1,1}(l) \end{bmatrix},$$

(1)

where 0 and 1 represent “idle” and “occupied” states, respectively. For example, $C_{0,0}(l)$ represents the transition probability from state “idle” in the current time slot to state “idle” in the next time slot. The probability of channel $l$ to be available for secondary user is equal to the steady state probability of channel $l$ to be at state “idle”, and can be obtained from

$$p_{l}^{\text{idle}} = \frac{1/C_{0,1}(l)}{1/C_{0,1}(l) + 1/C_{1,0}(l)},$$

(2)

where $p_{l}^{\text{idle}}$ is the available probability of channel $l$.

B. Sensing and Accessing Strategy of Secondary Users

If in the current time slot, the secondary user cannot access the channel due to the occupancy by the primary user, we assume that in the next time slot the secondary user will always attempt to access the same channel.$^1$ This channel handoff is called always-stay scheme [6]. Let $l_n(k)$ denote the channel that the secondary user $n$ wants to access at the $k$th time slot, then the always-stay scheme can be expressed as follows:

$$l_n(k) = l_n(k+1), \quad k \in \{1, 2, \ldots, k_{ub} - 1\},$$

where $k_{ub}$ represents the last time slot.

If in a certain time slot, the channel $l$ is idle, we assume that a secondary user has a probability of $p_{l}^{\text{idle}}$ to obtain the control of the channel $l$ due to contention with other secondary users which also attempt to access the same channel. This probability is obtained from

$$p_{l}^{\text{idle}} = 1 - \frac{n_l - 1}{n_l},$$

(3)

where $n_l$ is the number of secondary users contending for channel $l$. We assume that in each time slot, at least one secondary user

$^1$A channel sensing is performed at the beginning of a time slot.
will win the contention and be able to access channel \( l \). Note that with always-stay handoff scheme, the number of secondary users using the same channel is constant during the time period to transmit meter data to DAU.

**C. Optimal Partition Algorithm for the Secondary Users**

There are \( L \) primary channels and \( N \) secondary users in the system model under consideration. The secondary users are divided into \( L \) groups \( \mathcal{O} = \{ n_1, n_2, \ldots, n_l, \ldots, n_L \} \), where \( \mathcal{O} \) represents the partition pattern, and \( n_l \) represents the number of secondary users in group \( l \) and \( \sum_{l=1}^{L} n_l = N \). The secondary users in group \( l \) will always attempt to access channel \( l \) according to the always-stay scheme. Once \( \mathcal{O} \) is fixed, an absorbing Markov chain can be established for each group to model the meter data transmission of the group members. With the absorbing Markov chain, the average packet loss probability, denoted by \( \mu \), can be obtained. Note that the detail of the absorbing Markov chain will be presented in Section III.

To search for the optimal \( \mathcal{O}^* \) which leads to the lowest packet loss probability \( \mu \), we propose a simple optimal partition pattern searching algorithm based on genetic algorithm [7]. The description of this algorithm is given in Algorithm 1.

**Algorithm 1 Optimal Partition Algorithm**

1. Initialize the first generation of partition patterns \( \{ \mathcal{O}_1, \mathcal{O}_2, \ldots, \mathcal{O}_i, \ldots, \mathcal{O}_l \} \)
2. repeat
3. for all \( \mathcal{O}_i \) in the current generation do
4. for all group \( l \) in \( \mathcal{O}_i \) do
5. Obtain \( p_l^c \) from (3) by using \( n_l \) in \( \mathcal{O}_i \)
6. Construct the absorbing Markov chain \( \mathcal{M}_l \) explained in detail in Section III
7. Compute the number of failed packets \( f_l^c \) (i.e., packet loss) for group \( l \) in \( \mathcal{O}_i \) using \( \mathcal{M}_l \) and time constraint \( k \)
8. end for
9. Compute average packet loss probability \( \mu^{(i)} \) for \( \mathcal{O}_i \) using \( \{ f_1^{(i)}, f_2^{(i)}, \ldots, f_L^{(i)} \} \)
10. end for
11. Record the best fitness value \( \mu^0 \# \) in the current generation
12. According to \( \{ \mu^{(1)}, \mu^{(2)}, \ldots, \mu^{(i)}, \ldots, \mu^{(I)} \} \) of current generation, genetic algorithm function uses selection rules, crossover rules or mutation rules to produce the next generation
13. until The best fitness value \( \mu^0 \# \) cannot be improved further
14. Obtain the optimal partition pattern \( \mathcal{O}^* \) and optimal average packet loss probability \( \mu^* \)

The partition pattern \( \mathcal{O}_i \) is treated as an individual in the genetic algorithm. Each element \( n_l \) in \( \mathcal{O}_i \) can be considered as gene and the lowest packet loss probability is the best fitness value here. Once the best fitness value \( \mu^0 \# \) cannot be improved, the optimal partition pattern \( \mathcal{O}^* \) and the lowest average packet loss probability \( \mu^* \) are found.

**III. QUEUEING ANALYSIS**

In this section, an absorbing Markov chain model is presented to derive the packet loss probability of a secondary user in group \( l \) in which the same model can be applied to secondary user in other groups. First, the state space is defined. The transition matrix is derived, and then the packet loss probability is obtained.

**A. State Space**

Multi-dimension absorbing Markov chain is used to model the meter data packet transmission of each secondary user and the channel state. The state space of this absorbing Markov chain is defined as follows:

\[
\Psi = \{(M, C); M \in \{0, 1, \ldots, M\}, C \in \{0, 1\}\},
\]

where \( M \) and \( C \) are the random variables representing the number of residual packets waiting for transmission, and the channel state, respectively. Here, \( M \) is the number of total packets that each secondary user needs to transmit, \( C \) is the channel state at each time slot whose value 0 refers to “idle” state and 1 refers to “occupied” state.

**B. Transition Matrix**

The state transition matrix \( P \) for describing the packet transmission of a secondary user can be expressed as follows:

\[
P = \begin{bmatrix}
P_{M,M} & \cdots & P_{M,m'} & \cdots & P_{M,0} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
P_{m,M} & \cdots & P_{m,m'} & \cdots & P_{m,0} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
P_{0,M} & \cdots & P_{0,m'} & \cdots & P_{0,0}
\end{bmatrix}
\]

The row of matrix \( P \) represents the number of packets waiting for transmission from secondary user to DAU. The matrix \( P_{m,m'} \) consists of the transition probabilities from state \( m \) to state \( m' \), i.e., when there are \( m \) packets remaining for transmission in the current time slot and \( m' \) packets remaining in the next time slot where \( m' \leq m \).

We assume that in each time slot, the data transmission of secondary user is successful if a channel is free, secondary user wins the contention with other users, and there is not packet transmission error. Therefore, we have

\[
P_{m,m'} = 0, \quad m' \neq m \quad \text{and} \quad m' \neq m - 1.
\]

In a certain time slot, if the secondary user in group \( l \) successfully transmits a packet, each element in the matrix \( P_{m,m'} \) (where \( m' = m - 1 \)) can be obtained as follows:

\[
p_{(m,c),(m-1,c')} = p_c^l (1 - p_c^l) p_{c,c'}, \quad c = 0,
\]

where \( c \) and \( c' \) represent the channel states in the current and next time slots, respectively. Therefore, \( p_{c,c'} \) is the channel state transition probability that can be obtained from (1). \( p_c^l \) is packet transmission error probability and \( c = 0 \) means that the channel is idle. Here \( m \) must not be 0. If \( m \) becomes 0, the secondary user finishes its meter data transmission, there is no transition,
and the process stops. As a result, the elements in matrix $p_{0,m'}$ can be obtained as follows:

$$p_{(0,e),(m',e')} = \begin{cases} 0, & m' \neq 0 \\ p_{e,e'}, & \text{otherwise}. \end{cases}$$ (8)

For the situations in which the secondary user in group $l$ fails to transmit a packet, it may be due to the reason that the state of channel $l$ is “occupied”, or the state is “idle” but either a transmission error occurs or another secondary user in group $l$ accesses the channel. Therefore, the elements in matrix $p_{m,m'}$ for $m \neq 0$ and $m' = m$ can be computed as follows:

$$p_{(m,e),(m',e')} = \begin{cases} p_{e,e'}, & e = 1 \\ 0, & \text{otherwise}. \end{cases}$$ (9)

where $p' = 1 - p_l^T + p_l^T (1 - p_r^T)$. $e = 1$ means that the current channel is occupied by the primary user.

From (6), (7), (8), and (9), the system state transition matrix $P$ is established.

C. Solving for Average Packet Loss Probability

The matrix $P$ can be also expressed in a standard form of absorbing Markov chain as follows [8]:

$$P = \begin{bmatrix} T & D \\ 0 & P_{0,0} \end{bmatrix}$$ (10)

where $T$ is a $M \times M$ matrix containing element of $p_{m,m'}$, and in the same way $D$ can be treated as $M \times 1$ matrix. $0$ is a row vector of zeros. Each row of matrices $T$ and $D$ represents a transient state where $m \neq 0$. The column vector $D$ represents the transition to absorbing state where $m' = 0$.

Using $\tau_l$, a row vector to denote the initial probability distribution over the transient states for secondary users in group $l$, and $\tau_l$ can be defined as $\tau_l = [pi_l^{idle}, 1 - pi_l^{idle}, 0, \ldots, 0]$, whose non-zero elements correspond to the initial state $m = M$. With the limited period of time with length $k$ time slots for a secondary user to transmit all meter data packets to DAU, the probability distribution over all transient states can be obtained as follows:

$$\tau_l^k = \tau_l \left( \prod_{k=1}^{k} T \right),$$ (11)

where $\left( \prod_{k=1}^{k} T \right)$ represents the multiplication of matrix $T$ for $k$ times. Elements in vector $\tau_l^k$ represent the probabilities of the number of remaining packet being $m = 1, \ldots, M - 1, M$ after lapse of $k$ time slots. The probability of system being at absorbing state after lapse of $k$ time slots can be computed as follows:

$$a_l^k = 1 - \tau_l^k 1,$$ (12)

where $1$ is a column vector of ones.

The average number of remaining packets at a secondary user in group $l$ after lapse of $k$ time slots can be obtained as follows:

$$m_l^{rem} = \frac{M}{\sum_{m=1}^{M} m \pi_l^k (m)}.$$ (13)

where $\pi_l^k (m)$ is the probability of $m \in \{1, \ldots, M\}$ packets remaining at a secondary user after lapse of $k$ time slots. This probability is an element of vector $\tau_l^k$.

After $k$ time slots, the packets which have not been transmitted are considered to be lost (due to the time constraint violation). Therefore, the average packet loss probability is obtained from $\mu_l = m_l^{rem}/M$ for a secondary user in group $l$. The average packet loss probability over all groups can be computed as follows:

$$\mu = \frac{1}{N} \sum_{l=1}^{L} \mu_l n_l.$$ (14)

Note that the optimal partition algorithm presented in Section II-C can be applied to achieve the lowest average packet loss probability.

IV. OPTIMIZATION OF COST FOR POWER SUPPLY

In this section, first we give the formulation of the power supply cost optimization problem. Then we discuss the impact of packet loss probability $\mu$ obtained in the previous section on the optimality of the optimization results.

A. Formulation of Cost Optimization Problem

Once packets from secondary users are delivered to the MDMS by the DAU, the MDMS will extract the information pertaining to power demand and power production capacity from CRPGF in the packets. Then, MDMS performs power supply cost optimization. The power demand can be described by the demand scenario $\omega \in \Omega$, where $\Omega$ is the scenario space for power demand. The power production capacity from CRPGF can also be described by the production scenario $\psi \in \Psi$, where $\Psi$ is the scenario space for power production capacity from CRPGF. The corresponding probabilities of the scenarios are denoted by $\pi_\omega$ and $\pi_\psi$. We define $D_\omega$ and $R_\psi$ as the amount of power demand and power production capacity of scenario $\omega$ and scenario $\psi$, respectively.

The optimization problem for minimizing the cost of power bought from power plant is formulated as follows:

$$\phi = \min_{x_g, y_g, \psi, \omega} \sum_{g=1}^{G} x_g p_g^{(c)}$$ (15)

$$\sum_{\omega \in \Omega} \pi_\omega \sum_{\psi \in \Psi} \pi_\psi \sum_{g=1}^{G} y_g \pi_\psi p_g^{(d)}$$

subject to

$$\sum_{g=1}^{G} (x_g + y_g \pi_\psi) \geq D_\omega - R_\psi, \forall \omega, \forall \psi \quad (16)$$

$$x_g + y_g \pi_\psi \leq C_g, \forall g, \forall \omega, \forall \psi \quad (17)$$

$$x_g \geq 0, y_g \pi_\psi \geq 0, \quad (18)$$

where $x_g$ is the amount of power reserved at unit commitment stage, and $y_g \pi_\psi$ is the amount of power required at economic dispatch stage from power plant $g$ under scenarios $\omega$ and $\psi$. $\phi$ is the total cost of power supply. $p_g^{(c)}$ and $p_g^{(d)}$ are the forward price and option price, respectively. $C_g$ is the maximum power supply capacity of power plant $g$, and $G$ is the total number of power plants. The objective in (15) is to minimize the total cost by summing costs of power supply from power plants at unit commitment and economic dispatch stages. The constraint in (16) guarantees
that the amount of power supply from power plants (i.e., at both unit commitment and economic dispatch stages) together with the amount of power production from generators in CRPGF is equal to or larger than the amount of power demand in all combinations of scenarios $\omega$ and $\psi$. The constraint in (17) ensures that the power supply of all power plants does not exceed the maximum capacities. The constraint in (18) ensures non-negative of the power supply.

**B. Estimation of Probability Distribution**

To solve the optimization problem defined in (15)-(18) and obtain the optimal decisions $x_g$ and $y_{g,\psi,\omega}$, both the probability distributions of the scenario for power demand and that of the scenario for renewable power production capacity from CRPGF have to be estimated.

The meter data transmitted from house and generator in CRPGF are the samples of the power demand and power production capacity, respectively. As in [3], the probability distributions of power demand and power production capacity are estimated from the available sampling data at MDMS. Let $\pi_{\omega}$ and $\pi_{\psi}$ denote the probabilities of power demand with scenario $\omega$ and power production capacity with scenario $\psi$ estimated at MDMS without any packet loss. However, in reality, the packet loss can occur due to the transmission error and time constraint of meter data transmission.

The estimated probabilities of scenarios with packet loss for power demand and power production capacity (i.e., $\tilde{\pi}_{\omega}$ and $\tilde{\pi}_{\psi}$, respectively) become

$$
\tilde{\pi}_{\omega} = \begin{cases} 
\pi_{\omega} + \mu \left( \sum_{\omega' \in \Omega, \omega' \neq 0} \pi_{\omega'} \right), & \text{if } D_{\omega} = 0 \\
(1-\mu)\pi_{\omega}, & \text{if } D_{\omega} > 0,
\end{cases} \quad (19)
$$

$$
\tilde{\pi}_{\psi} = \begin{cases} 
\pi_{\psi} + \mu \left( \sum_{\psi' \in \Psi, \psi' \neq 0} \pi_{\psi'} \right), & \text{if } R_{\psi} = 0 \\
(1-\mu)\pi_{\psi}, & \text{if } R_{\psi} > 0.
\end{cases} \quad (20)
$$

**C. Cost of Packet Loss**

After the estimated probability distributions of $\tilde{\pi}_{\omega}$ and $\tilde{\pi}_{\psi}$ with packet loss are obtained, from (15)-(18), we can obtain the optimal decisions for power supply (i.e., $\tilde{x}_g$ and $\tilde{y}_{g,\psi,\omega}$) under packet loss by replacing $\pi_{\omega}$ and $\pi_{\psi}$ with $\tilde{\pi}_{\omega}$ and $\tilde{\pi}_{\psi}$, respectively. The actual total cost of power supply with packet loss becomes

$$
\tilde{\phi} = \sum_{g=1}^{G} \tilde{x}_g p^{(c)}_g + \sum_{\omega \in \Omega} \sum_{\psi \in \Psi} \tilde{\pi}_{\omega} \tilde{\pi}_{\psi} \sum_{g=1}^{G} \tilde{y}_{g,\psi,\omega} p^{(d)}_g. \quad (21)
$$

Therefore, the cost of packet loss is obtained from $\delta = \tilde{\phi} - \phi$ where $\phi$ is the total cost of power supply without packet loss obtained from (15).

**V. PERFORMANCE EVALUATION**

**A. Parameter Setting**

In a service area, we assume that there are 100 secondary users including 80 smart meters in houses and 20 smart meters in generators of CRPGF. There are three primary channels. The average power demand of each house is random with mean of 3kWh, and the average amount of renewable power that each generator can produce is random with mean of 2kWh. The scenario space of power demand $\omega$ is defined as $D_\omega \in \{0\text{kWh}, 1\text{kWh}, \ldots, 500\text{kWh}\}$. The scenario space of power production capacity $\psi$ is defined as $R_\psi \in \{0\text{kWh}, 1\text{kWh}, \ldots, 100\text{kWh}\}$. We assume that the number of packets that each secondary user needs to transmit is $M = 5$. The packets contain the updated meter data once the weather changes or the power demand from the customers changes. The limited time period for meter data transmission (i.e., time constraint) is varied between 80 and 400 time slots. The length of each time slot is 200 ms. The available probabilities of these three channels are given as $p_{ch1} = 0.2$, $p_{ch2} = 0.5$, and $p_{ch3} = 0.8$. The transmission error probability is 0.1. The forward price is $p^c_{g} = 0.3$ per kWh and the option price is $p^{(d)}_{g} = 0.5$ per kWh. Only one traditional power plant (i.e., $G=1$) is assumed to provide electric power at both unit commitment and economic dispatch stages.

**B. Numerical Results**

1) **Impact of Number of Secondary Users on the Packet Loss Probability:** Fig. 2 shows the average packet loss probability under different number of secondary users. As expected, when the number of secondary users increases, the packet loss probability increases. Since when the number of secondary users increases, more contentions among them will happen. Consequently, the secondary users will have less chance to transmit their packets successfully.

![Fig. 2. Impact of number of secondary users on the packet loss probability.](image)

2) **Impact of Channel Available Probability on the Packet Loss Probability:** Fig. 3 shows the average packet loss probability under different time constraints. As expected, when the length of time constraint increases, the packet loss probability decreases...
since there are more available time slots for transmitting the packet from secondary users. In Fig. 3, the legend “available probabilities settings 1, 2 and 3” represent the cases of available probabilities of the three channels to be \{0.2, 0.5, 0.8\}, \{0.2, 0.2, 0.8\}, and \{0.2, 0.8, 0.8\}, respectively. It shows that higher average available probability of three primary channels will result in lower packet loss probability, since there is higher chance of channel to be free from primary users and can be accessed by the secondary users.

![Fig. 3. Impact of channel available probability on the packet loss probability.](image)

3) Impact of Time Constraint on the Cost: Fig. 4 shows the power cost from unit commitment stage, from economic dispatch stage, and total cost under different time constraints. As the length of time constraint increases, the packet loss probability decreases which allows the estimation on the power demand distribution and the power production capacity distribution of secondary users to be more accurate. As a result, it can be observed that more power can be reserved at the commitment stage (Fig. 4(a)) which has cheaper forward price. As a result, the power cost due to economic dispatch stage with expensive option price decreases (Fig. 4(b)), and hence, the total power cost decreases (Fig. 4(c)).

![Fig. 4. Impact of time constraint on the cost including revenue from renewable power.](image)

VI. CONCLUSION

Cognitive radio network can be a sensible choice for the wireless communication for transmitting the meter data (i.e., power demand and production) to the data aggregator unit. However, the meter data transmission can have the time constraint which affects the packet loss (i.e., the meter data collected after deadline is considered to be lost). In this paper, we have used absorbing Markov chain to model the process of meter data transmission from smart meters embedded in power consumer nodes (i.e., houses) and power production nodes (i.e., generator in community renewable power generation facility) to the DAU. Smart meter performs dynamic spectrum access to transmit meter data on the licensed channel opportunistically. In addition, the effect of the packet loss to the power supply cost optimization has been analyzed. In the performance evaluation, the results have clearly shown that the parameters of dynamic spectrum access can affect the cost of power supply in the smart grid environment. For the future work, the multiple service areas with overlapping primary channels will be considered.

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