SWIM: Social Welfare Maximizing Incentive Mechanism for Smart Meter Data Aggregation

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***Abstract*—In spite of many benefits, e.g., energy and communication cost efficient data aggregation, in-network data aggregation network in the smart meter network involves some smart meters acting as relays. Unlike wireless sensor networks (WSNs), the aggregator in the smart meter network cannot assign smart meters as a relay at its will, unless it properly rewards them. Therefore, to encourage users to contribute their smart meters to be used as relays, we introduce an incentive mechanism for the smart meter data aggregation. Unlike the existing incentive mechanisms where the value of completing a requested task is assumed to be fixed regardless of who takes the requested task, we formulate the winner selection problem by incorporating an additional value that depends on who takes the task. Based on the additional value, called "derivative value", we propose a Social Welfare maximizing Incentive Mechanism (SWIM) for the smart meter data aggregation. SWIM not only encourages users to contribute their smart meters to be used as relays by rewarding them with incentives, but also enhances overall satisfaction of participating smart meters by maximizing the social welfare of the system. Simulation results show that SWIM achieves better social welfare of the system and utility of the aggregator compared with the existing incentive mechanisms.**

***Index Terms*—Smart Meter; Incentive; Data Aggregation; Social Welfare.**

I. INTRODUCTION

Among many important components of the smart grid, the smart meter is one of the most fundamental and essential component in the smart grid system. It digitally records the amount of resource consumption, e.g., electric energy, gas, and water and delivers the recorded data to the main grid, which enables many critical functions of the smart grid, such as load monitoring and billing. Through load monitoring and billing, Demand-Response (DR), or Demand-Side (DS) management can be realized, which enables a demand-supply balance between users and the grid to ultimately reduce the excessive power generation and green gas emission [1].

As the smart meters emerge as the key component of the smart grid, the number of the smart meters installed all over the world has been drastically increasing. For example, there are more than 50 million smart meters installed in the US as of July, 2014 and the number is expected to grow continuously [2]. However, along with the quantitative growth of the smart meters, the ever-increasing volume of the smart meter data and the energy consumption of the smart meter networks emerge as new challenges. Therefore, how to efficiently aggregate the smart meter data has attracted much research attention from the academia and industries. To address the challenges, many researchers have taken into consideration the in-network data aggregation in the smart meter network [3] [4]. However, existing works assume that the aggregator can assign any smart meter as a relay at will, which is not so practical in the real smart meter networks. Unlike the sensors in wireless sensor networks (WSNs), the smart meters reflect users' rationality and selfishness. In the smart meter network, users may not contribute their smart meters to be used as relays to avoid potential loss, unless they are given some form of incentives. In other words, unlike in WSNs, the aggregator in the smart meter network has to incentivize users to contribute their smart meters to be used as relays, rather than just assigning them at will. Therefore, to encourage the users to contribute their smart meters to be used as relays, we introduce an incentive mechanism for the smart meter data aggregation. For the incentive mechanism design, we refer to various incentive mechanisms, especially those from the crowdsourcing. However, the existing incentive mechanisms for crowdsourcing assume that the value of completing a requested task is fixed, no matter which worker takes the requested task. In the smart meter network, though immanent but unperceived, there exists some additional value, e.g., reduced energy consumption depending on which smart meter takes the task (acting as a relay), on top of the fixed value of submitting the data itself.

To the best of our knowledge, this is the first work that considers the additional value that depends on who takes the task. In this work, to incorporate the notion of the additional value into the incentive mechanism for the smart meter data aggregation, we present a novel concept of "derivative value" and further develop it into "competition value". Additionally, we formulate the overall value in the smart meter network as "social welfare". Rather than maximizing the utility of the aggregator, our incentive mechanism maximizes the social welfare, in order to enhance the overall satisfaction of participating smart meters. The rest of this paper is organized as follows. In Section II, we present the related works. In Section III, we provide our system model. In Section IV, we introduce the derivative value and competition value for the winner selection process. In Section V, we design SWIM, a social welfare maximizing incentive mechanism. In Section VI, we evaluate our incentive mechanism for the smart meter data aggregation. Finally, we conclude this paper in Section VII.

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II. Related Work

A. In-network Data Aggregation

In-network data aggregation was first proposed to combine and deliver the data distributed over and collected from many sensors (sources) to a destination node efficiently in terms of the energy and communication cost. In-network aggregation handles not only how data is aggregated at each sensor node but also how data is delivered through the network, which significantly affects the energy consumption and the overall network efficiency. The in-network aggregation can be categorized into three main approaches: (1) tree-based approach, (2) cluster-based approach, and (3) multipath approach.

1) Tree-based approaches build a spanning tree where an aggregator is residing on the root of the tree. Using the hierarchical organization of sensor nodes, a tree-based approach can simplify the data aggregation flowing from the sources to the destination. In the spanning tree, each node delivers the sensing data, combined with the data from its children, to its parent node, which will eventually lead to the delivery of every data in the network to the root node (the aggregator) [5] [6]. However, the tree-based approaches have the robustness problem where the data delivery will fail if the node's parent-node does not operate normally.
2) Cluster-based approaches are quite similar to the tree-based approaches. However, cluster-based schemes partition nodes into clusters. In addition, each cluster has a special node, named "cluster head", responsible for the intra-cluster data aggregation and the transmission of the aggregated data to the aggregator. That is, a cluster head acts as a relay node for the other nodes in the same cluster [7] [8]. As in the tree-based approaches, the cluster-based approaches enable the simple data aggregation and also have the robustness problem.
3) Multipath approaches were proposed as a solution to the robustness problem of both the tree-based approaches and the cluster-based approaches. In a multipath approach, as the name suggests, a node broadcasts data to a number of neighboring nodes, rather than sending its own data or the aggregated data to a single parent. By doing so, a source node can have multiple data flows to the destination, which enables to achieve higher robustness since the data can be delivered even when some of the multiple flows fail. However, multipath approaches achieve the robustness at the cost of some extra overhead resulting from the excessive data transmission [9] [10].

In the smart meter network, since every smart meter estimates the amount of resource consumption and transmits the data to the aggregator(s), the smart meter network shares some similar characteristics with the wireless sensor network. The similarity has led to various research works that apply in-network aggregation to the smart meter network.

B. Incentive Mechanisms for Crowdsourcing

In recent years, many incentive mechanisms for crowdsourcing have been proposed. Yang et al. [11] present two generic but concrete system model of incentive mechanisms for crowdsourcing: the platform-centric model, and the user-centric model to motivate mobile users to participate in the crowdsensing system. D. Peng et al. [12] propose a quality based incentive mechanism for crowdsensing, where the platform rewards the participants proportionally to their contribution, to motivate the rational participants to perform sensing tasks efficiently. C. Liu et al. [13] propose a Quality of Information (QoI)-aware incentive mechanism for participatory sensing to maximize the quality of information by maximizing the user participation in the system. S. Ji et al. [14] present an incentive mechanism for mobile phones with uncertain sensing time. Lee and Hoh [15] propose a Reverse Auction based Dynamic Pricing incentive mechanism with Virtual Participation Credit (RADP-VPC) to maintain participants and promote dropped users to participate again in order to retain sufficient number of participants for the required service quality. However, the existing works assume that the value derived from completing a requested task is fixed, no matter which provider takes the requested task. In other words, the influence range of completing the requested task is confined to the interaction only between the platform (requester) and the *winner providers* who receive the payment for completing the task. Therefore, technically speaking, which provider is selected as a winner does not affect the other loser providers' utilities. However, in reality, some additional values can be derived from which provider takes the task, besides the value of completing the requested task itself.

III. System Model

In this section, we present the system model of our incentive mechanism for the smart meter data aggregation. The system structure is in a form of reverse auction where the roles of buyers and providers are reversed. That is, in our system, providers (smart meters) compete to obtain the data aggregation task (acting as a relay) from the buyer (aggregator) and rewards will decrease as the providers compete with each other. In our system model, there are an aggregator, a platform, and a set of N smart meters, $\mathcal{W} = \{1, 2, 3, \cdots, i, \cdots, N\}$ that act as providers in the smart meter data aggregation. Figure 1 illustrates the relay appointment in the smart meter network. We make following assumptions to reflect the real smart meter network.

1) The platform can obtain the location information of every smart meter.
2) Each smart meter has a limited capacity to aggregate data. That is, each smart meter has the maximum number of smart meters S_{max} that it can support as a relay.

For the smart meter data aggregation, the aggregator posts a set of M data aggregation tasks, $\mathcal{T} = \{1, 2, 3, \cdots, j, \cdots, M\}$ on the platform where each task j has the corresponding value, $v_j \in \mathbb{R}^+$ to the aggregator. With the second assumption taken

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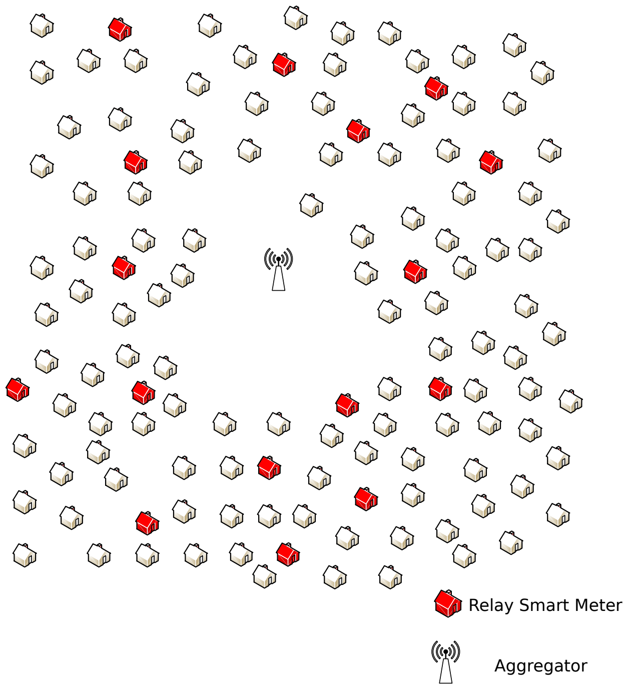

Figure 1. Relay Appointment in Smart Meter Network

into consideration, the aggregator determines the size of the set of tasks, $M \in \mathcal{Z}^+$, which is calculated as

$$M \geq \frac{N}{(S_{max}+1)}. \quad (1)$$

Given $\mathcal{T}$, the platform announces the data aggregation task information to all the participating smart meters. In response to the announcement, each smart meter i submits its type information θ_i to the platform. Each type information θ_i consists of smart meter i's id id_i and bid information b_i. In the process of completing its assigned data aggregation task, smart meter i has an associated cost, $c_i \in \mathbb{R}^+$. Since each smart meter is rationally selfish, each participating smart meter i submits its bid price $b_i \geq c_i$ and decides to work on the requested task only if it is paid with $p_i \geq b_i$. Therefore, when $\mathcal{W}_s$ denotes the set of selected smart meters, the utility of smart meter i is defined as

$$u_i = \begin{cases} p_i - c_i & \text{if } i \in \mathcal{W}_s \\ 0 & \text{otherwise} \end{cases}. \quad (2)$$

Given the set of data aggregation tasks $\mathcal{T}$ and the set of smart meters $\mathcal{W}$, the platform determines a subset of smart meters which will act as relays for the data aggregation tasks $\mathcal{T}$ and calculates the payment p_j to each relay smart meter of task j. For the aggregator, the payment to the winner smart meters is the cost of completing the data aggregation tasks. Thus, the utility of the aggregator is calculated as

$$u_0 = \sum_{j \in \mathcal{T}} v_j - \sum_{i \in \mathcal{W}_s} p_i. \quad (3)$$

In our incentive mechanism, we aim to achieve the following four desirable economic properties: (1) individual rationality, (2) budget-balance, (3) computational efficiency, and (4) truthfulness. The descriptions of each property are provided below.

- **Individual Rationality**: each participating worker has a non-negative utility as $u_i \geq 0$, where u_i is the utility of entity i.
- **Budget-balance**: the budget assigned to the platform can cover all the payment to the winning providers as $\sum_{i \in \mathcal{W}_s} p_i \leq B$.
- **Computational Efficiency**: the winner selection mechanism can be computed in polynomial time.
- **Truthfulness**: no provider can improve its utility by submitting a false cost information. In other words, submitting the true cost information is the dominant strategy for all smart meters.

According to Myerson [16], in order to guarantee truthfulness in a reverse auction system, an auction mechanism should satisfy the following two conditions. First, the winner selection process in the auction is monotone, which means that if provider i wins the auction by bidding b_i, he or she will surely win the auction by bidding $b_i' \leq b_i$. Second, the winner in the auction is rewarded with the critical value, which is defined as the maximum payment a seller can ask, while winning the auction.

IV. Derivative Value and Competition Value

As in the existing incentive mechanisms, the value of submitting the aggregated data itself is fixed. However, on top of the fixed value, we take into consideration some additional value that depends on which smart meter takes the task, called "derivative value". The derivative value matrix of the requested data aggregation task j is defined as

$$\Delta v^j = \begin{bmatrix} \Delta v^j_{11} & \Delta v^j_{12} & \Delta v^j_{13} & \cdots & \Delta v^j_{1N} \\ \Delta v^j_{21} & \Delta v^j_{22} & \Delta v^j_{23} & \cdots & \Delta v^j_{2N} \\ \Delta v^j_{31} & \Delta v^j_{32} & \Delta v^j_{33} & \cdots & \Delta v^j_{3N} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \Delta v^j_{N1} & \Delta v^j_{N2} & \Delta v^j_{N3} & \cdots & \Delta v^j_{NN} \end{bmatrix}, \quad (4)$$

where each matrix element Δv^j_{iq} denotes smart meter q's derivative value when smart meter i is the winner for task j, and $\Delta v^j_{ii} = 0, \forall i \in \mathcal{W}$. When smart meter i is selected as the winner, the derivative value of requested task j is defined as

$$\Delta v^j_i = \sum_{q \in \mathcal{W}} \Delta v^j_{iq}. \quad (5)$$

In other words, assuming smart meter i is the winner for task j, the derivative value of task j is the sum of all the matrix elements in the i-th row. To incorporate the derivative value in the winner selection process, we introduce a "competition value" of smart meter i for task j, which is defined as

$$v^j_i = v_j + \Delta v^j_i, \quad (6)$$

where v_j is the value of submitting the aggregated data of task j itself. In the winner selection process, the smart meter with a higher competition value and a lower bid has a higher probability to win the competition. Additionally, we define "social welfare" of the system as

$$W(1 \sim N) = \sum_{j \in \mathcal{T}} \Delta v_*^j - \sum_{i \in \mathcal{W}_s} p_i, \tag{7}$$

where Δv_*^j denotes the derivative value of the winner smart meter for task j. That is, the social welfare of the system is the sum of all selected smart meters' derivative values minus the sum of the payments for them. In this work, rather than maximizing the utility of the platform, we set the objective of the platform as maximizing the social welfare, in order to enhance the overall participating smart meters' satisfaction.

V. The Design of SWIM

In this section, we present SWIM, a Social Welfare maximizing Incentive Mechanism for the smart meter data aggregation to enhance the overall satisfaction of participating smart meters, and prove that the incentive mechanism satisfies all the desirable economic properties. The incentive mechanism consists of two algorithms: (1) k-means clustering algorithm, and (2) winner selection algorithm.

A. *k-means Clustering Algorithm*

Given the set of data aggregation tasks ($\mathcal{T}$) and the set of type information from participating smart meters (θ), the platform runs k-means clustering algorithm [17]. As we assumed in the system model, the platform retains the location information of every smart meter. For simplicity, we also assume that data transmission blockage by buildings is negligible. By mapping the identification number of each smart meter to the corresponding location information, the platform can locate each participating smart meter. In this work, we assume that the location information of smart meter i contains a pair of its x-coordinate and y-coordinate. Using this location information, the platform runs k-means clustering algorithm. Since the aggregator has M data aggregation tasks, the platform sets k to M to divide participating smart meters into a set of M clusters, $G = \{G_1, G_2, G_3, \cdots, G_j, \cdots, G_M\}$ to minimize the intra-cluster distance variance, defined as the sum of square of distance between each smart meter in a cluster and the centroid of the cluster, which is equal to all the energy consumption for the data transmission within the cluster.

B. *Winner Selection Algorithm*

In the winner selection algorithm, the objective of the platform is to maximize the social welfare of the system. The algorithm is divided into two steps: winner selection step, and payment step.

Step 1 - Winner Selection: To achieve the objective, for each cluster G_j, the platform selects the smart meter with the minimum bid to competition value ratio (b_i/v_i^j) as the candidate for the relay smart meter for data aggregation task j. The winner selection step is the same as the greedy mechanism which selects the smart meter with the minimum bid to competition value ratio as a winner. The mechanism is known to be computationally efficient. Note that in the winner selection rule, the platform does not determine the winner smart meter, but just the candidate smart meter.

Step 2 - Payment: After selecting a candidate smart meter, the platform decides the payment to the candidate, which is defined as $p_j = \max\{p_j, \frac{b_c}{v_c^j} v_{i^*}^j\}$. Here, the payment p_j in our payment step is the critical value for smart meter i^* when smart meter i^* is the candidate of G_j. According to the winner selection step, when smart meter c satisfies the following chains of inequations

$$\frac{b_c}{v_c^j} \leq \frac{b_1}{v_1^j} \leq \frac{b_2}{v_2^j} \cdots \leq \frac{b_{|G_j|-1}}{v_{|G_j|-1}^j}, \tag{8}$$

the platform selects smart meter c as the winner smart meter for G_j. If smart meter i newly joins the cluster G_j and wants to win the auction, it must assign its bid as

$$b_i \leq \frac{b_c}{v_c^j} \times v_i^j. \tag{9}$$

Otherwise, the platform selects smart meter c as the winner smart meter instead of smart meter i according to the winner selection step. After calculating the payment to the candidate smart meter, the platform checks the budget-balance. If the payment is affordable, the platform determines the winner and updates the budget. Otherwise, the platform discards the candidate smart meter and repeats the winner selection rule until it finds the winner in the rest of smart meters or none of the smart meters in the cluster budget-feasible. The detail of the winning requester selection algorithm is presented in Algorithm 1.

Algorithm 1: Winner Selection Algorithm

Input : θ, Γ, B
Output: $\mathcal{W}_s$

$\mathcal{W}_s \leftarrow \emptyset$, $p_{1\sim M} \leftarrow 0$;
G=k-means Clustering(θ, $|\Gamma|$);
for $G_j \in G$ **do**
  while $p_j = 0$ **do**
    $i^* \leftarrow \arg\min_{i \in G_j} \frac{b_i}{v_i^j}$;
    $G_j \leftarrow G_j \setminus \{i^*\}$;
    $c \leftarrow \arg\min_{i \in G_j} \frac{b_i}{v_i^j}$;
    $p_j \leftarrow \max\{p_j, \frac{b_c}{v_c^j} v_{i^*}^j\}$;
    if $B - p_j \geq 0$ **then**
      $B \leftarrow B - p_j$;
      $\mathcal{W}_s \leftarrow \mathcal{W}_s \cup \{i^*\}$;
    else
      $p_j \leftarrow 0$;
    end
  end
end
return $\mathcal{W}_s$

C. *Economic Properties*

In this subsection, we provide the proofs for the desirable economic properties of SWIM.

Lemma 1. *SWIM is individually rational.*

Proof. As we assumed in the system model, each participating smart meter i submits its bid price $b_i \geq c_i$ to compensate the associated cost, and decides to work on the requested task only if it is paid with $p_i \geq b_i$. Thus, the utility of winner smart meter i is $u_i = p_i - c_i \geq p_i - b_i \geq 0$. For the loser smart meter, the utility is simply 0. □

Lemma 2. *SWIM is budget-balanced.*

Proof. In the payment step, given the candidate for the relay smart meter, the platform checks whether the budget can cover the payment to the candidate. If the payment is not affordable by the current budget, the platform discards the candidate and repeats the winner selection rule. This step guarantees that the payment to the winner smart meters is always decided within the budget constraint. □

Lemma 3. *SWIM is computationally efficient.*

Proof. Except for k-means clustering, the winner selection algorithm takes $\mathcal{O}(MN^2)$ time since the winner selection step and the payment step take $\mathcal{O}(N^2)$ for each cluster G_j and the winner selection algorithm runs for G whose size is M. □

Lemma 4. *SWIM is truthful.*

Proof. According to [16], we need to prove that our winner selection step satisfies the two conditions, the monotonicity of the winner selection and the critical value based payment to winners. The monotonicity of the winner selection step is obvious, since if smart meter i wins the auction by bidding b_i, he will be surely selected as winner by bidding $b'_i \leq b_i$. For the critical value based payment, the payment step of SWIM calculates the critical value and set the value as the payment. If smart meter i submits $b_i > p_i$, he will lose the auction and be replaced. Therefore, p_i is the critical value. □

By Lemmas 1 to 4, we have Theorem 1 as follows:

Theorem 1. *SWIM is individually rational, budget-balanced, computationally efficient, and truthful.*

VI. EVALUATION

In this section, we evaluate our incentive mechanism, SWIM, and compare its social welfare to that of the existing incentive mechanism [18] whose winner selection process is also based on the greedy algorithm, while only taking the fixed value of submitting the aggregated data itself into consideration for the winner selection. For evaluation, we use MATLAB.

A. Simulation Setup

We assume that all the smart meters are randomly distributed in a 2000 m by 2000 m region and the aggregator is located at (1000, 2500), when the vertices of the region are (0, 0), (0, 2000), (2000, 0), and (1000, 2500). In the simulation, we define the cost c_i of smart meter i as the additional data transmission energy needed to act as a relay. To set the cost, we adopt the data transmission energy consumption model from [19]. According to the model, the smart meter consumes E_{elec} in a unit of nJ/bit to operate the transmitter or the receiver and E_{amp} in a unit of pJ/bit/m^2 to run the amplifier. Then, the amount of energy expended to send l-bit data a distance d is calculated as

$$P_{TX}(l,d) = E_{elec}l + E_{amp}ld^2. \qquad (10)$$

For simplicity, we approximate $P_{TX}(l,d)$ to

$$P_{TX}(l,d) \approx E_{amp} \times l \times d^2, \qquad (11)$$

because d affects much more significantly to the transmission energy. In the simulation, we set $E_{amp} = 100\ nJ/bit/m^2$ and $l = 8000$ bits. For the fixed value of submitting the smart meter data, we set the same value $v = 10$ for every smart meter. That is, v_j, the fixed value of completing the smart meter data aggregation task j for G_j is $|G_j| \times 10$ when the number of smart meters in G_j is the size of G_j. In the simulation, we define the derivative value Δv^j_{iq} as the data transmission energy saving of smart meter q when smart meter i is the winner for task j. As the energy saving is in the unit of J, we convert 10 J to the unit value ($v = 1$).

B. Simulation Results

1) Social Welfare Increment: Figure 2 shows the social welfare increment by incorporating the derivative value in the winner selection process in comparison with [18]. Figure 2a shows the social welfare increment corresponding to the number of participating smart meters. Results show that regardless of the system size (the number of participating smart meters), the social welfare increment is positive, which means that a higher social welfare is obtained by considering the derivative value in the winner selection process. The higher social welfare results from selecting more profitable (in terms of social welfare) smart meters as relays as well as rewarding them with less payment than [18], while still satisfying the individual rationality of each smart meter. Results also show that as the system size increases, the social welfare increment per cluster decreases. The reason for the decrease in the social welfare increment comes from the density change of smart meters in the simulation region. As the density increases, the difference between the transmission distance to the aggregator and that to a relay smart meter becomes less, which consequently results in the less transmission energy saving. Figure 2b shows the social welfare increments corresponding to the increasing S_{max}. Results show that regardless of S_{max}, a higher social welfare is obtained by considering the derivative value in the winner selection process. The reason for the higher social welfare is the same as that of the system size. Results

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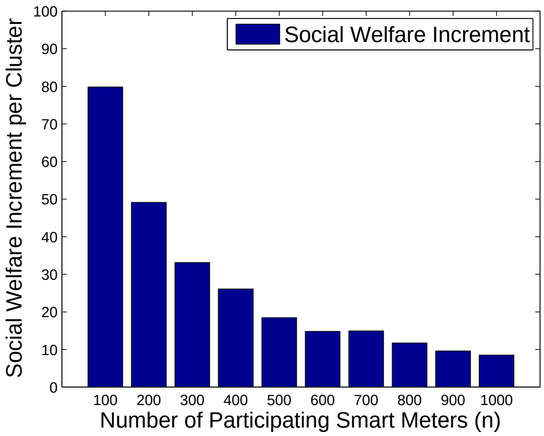
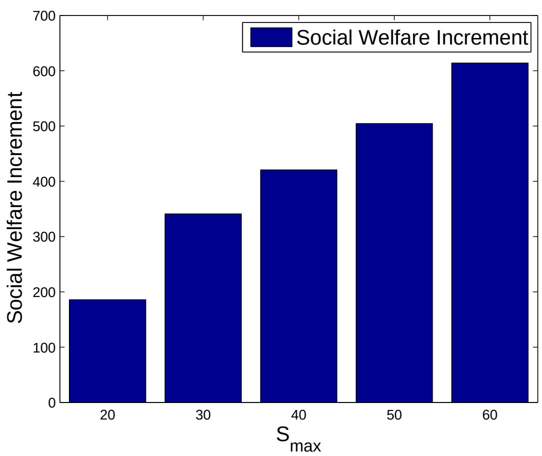
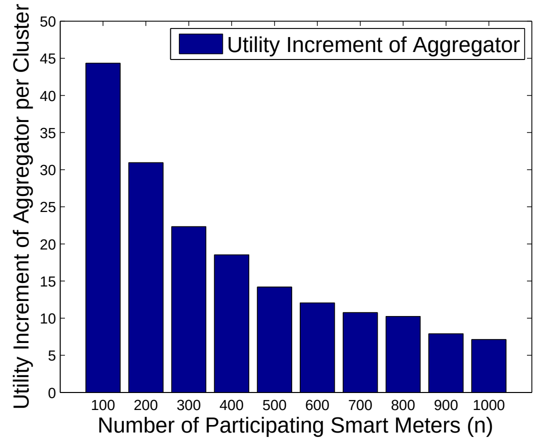


(a) Impact of System Size on Social Welfare (S_{max}=30)

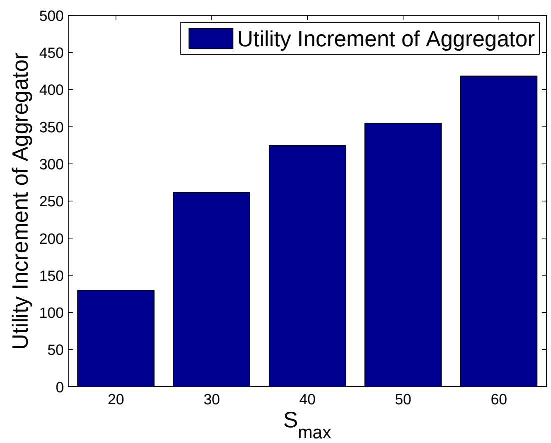


(b) Impact of S_{max} on Social Welfare (n=500)

Figure 2. Social Welfare Increment



(a) Impact of System Size on Aggregator's Utility



(b) Impact of S_{max} on Aggregator's Utility

Figure 3. Utility Increment of Aggregator

also show the tendency that with higher S_{max}, the system can obtain higher social welfare. Therefore, as S_{max} increases, the aggregator can achieve a larger gap between the derivative value increment and the payment to the winner smart meters. The tendency results from a relatively lower increase rate of the payment corresponding to S_{max} in comparison to that of the derivative value. Assuming one aggregator can cover 500 smart meters, we can achieve an increment of 300 in the social welfare, which amounts to 3000 J. Then, if smart meters transmit data every 15 minutes, we can save 288,000 J per day from 500 smart meters. Applying the calculation result to the number of smart meters installed in the US as of 2014 [2], we can save 28.8 GJ of energy for smart meters in the US. Moreover, if we can deploy smart meters with a higher S_{max}, the smart meter network can achieve even more energy saving.

2) Utility Increment of Aggregator: Figure 3 shows the utility increment of the aggregator by incorporating the derivative value in the winner selection process, in comparison with [18]. The simulation settings are the same as those of social welfare increment. Figure 3a shows that regardless of the system size (the number of participating smart meters), the aggregator achieves the higher utility by considering the derivative value in the winner selection process. According to (3), the utility of the aggregator u_0 is only affected by p_i since v_i for each smart meter has the same value. Thus, unlike the case of social welfare increment, the higher utility of the aggregator only results form achieving narrower gaps between c_i and $p_i, \forall i \in \mathcal{W}_s$ than [18], while still satisfying the individual rationality of each winner smart meter. Results also show that as the system size increases, the utility increment of the aggregator per cluster decreases. The downturn in the utility increment indicates that as the density of smart meters increases, the gap between p_i of SWIM and that of [18] becomes narrower. Figure 3b shows that regardless of S_{max}, the aggregator achieves the higher utility by considering the derivative value in the winner selection process. Results also show that with a higher S_{max}, the aggregator can obtain a higher utility. Such tendency indicates that the aggregator can achieve higher cost-effectiveness by appointing the smart meters with a higher S_{max} as relays. The reason for the tendency is that the reward which will be given to newly appointed smart meters is more expensive than that of the existing relay smart

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meters for the increment of data aggregation coverage.

VII. Conclusion and Future Work

In this paper, we propose SWIM, a social welfare maximizing incentive mechanism for the smart meter data aggregation. SWIM encourages users to contribute their smart meters to be used as relays for the smart meter data aggregation system by rewarding the relay smart meters. In order to enhance the overall satisfaction of participating smart meters, SWIM maximizes the social welfare of the system, rather than maximizing the utility of the aggregator. On top of the fixed value of submitting the smart meter data itself, SWIM incorporates some additional value derived from the data aggregation process, named "derivative value", in the winner smart meter selection process. We prove that SWIM achieves individual rationality, budget-balance, computational efficiency, and truthfulness. Simulation results show that our incentive mechanism achieves better social welfare of the system and the utility of the aggregator, compared to the existing incentive mechanisms. As a future work, we will consider the data aggregation in the multi-hop heterogeneous relay smart meter network where smart meters have different data transmission distances and S_{max}.

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