Incentive Mechanism Design for Electricity Data Trading With Data Valuation-Aware Contract

Liya Ma, Hongxun Hui, Yonghua Song
State Key Laboratory of Internet of Things for Smart City, Department of Electrical and Computer Engineering,
University of Macau, Macao, China
hongxunhui@um.edu.mo

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***Abstract*—With more generation fluctuations from the high penetration of renewable energies, dispatching large-scale demand-side resources becomes crucial in maintaining the power system balance between supply-side and demand-side. It puts forth significantly greater data requirements compared with traditional power systems, e.g. explosive data volume and highly frequent data collection between the data aggregators (DAs) and the data service operator (DTSO). Preferred by the DTSO, higher-value data with better data quality and timeliness will bring more benefits to the real-time dispatching of the demand-side resources than lower-value data. Thus, the data should be collected, transmitted, and traded in accordance with their varying values across different DAs. To resolve this issue, this paper proposes an incentive mechanism for electricity data trading between DAs and the DTSO, incorporating a data valuation-aware contract. First, we develop a data valuation model considering the data quality and timeliness. Then, taking into account the diverse value of data across DAs, we design a trading volume-reward bundled contract for DAs. The DTSO provides DAs with varying rewards to obtain higher-value data. Finally, the effectiveness of the proposed mechanism is validated using realistic data.**

***Index Terms*—Data trading, incentive mechanism, data valuation, trading volume-reward bundled contract.**

I. Introduction

THE rapid increase of renewable generators brings large amounts of fluctuating power output in the power system. The fluctuations result in gradual attention to the power system balance between the demand and supply sides [1]. Thus, regulation resources are becoming critical to maintain the system balance. Demand-side resources have considerable regulation potential due to *i*) a large account for power consumption; *ii*) the ability of energy storage. It follows to be a promising scheme by dispatching demand-side resources to provide regulation resources in multiple ancillary service scenarios, including frequency regulation, primary reserve, and synchronized reserve, et al [2].

Generally, the regulation capacity of an individual demand resource is much less than that of an individual traditional power generator. Thus, large-scale demand-side resources should be dispatched to provide significant regulation effects, which will cause explosive data [3]. Besides, highly frequent data collection is required in ancillary services. The primary and synchronized reserve require that the resources should collect the data 5 times in each 5-minute interval at a frequency of one minute [4]. More severely, the frequency regulation requires that resources should collect the data 30 times in each 5-minute interval at a frequency of 10 seconds [5].

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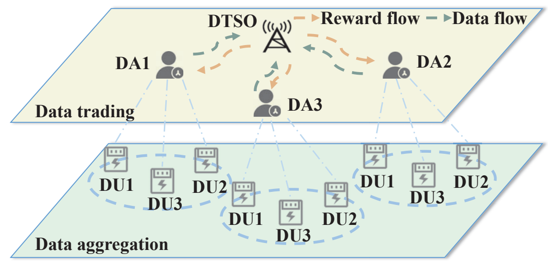


Fig. 1. The structure of data trading.

The explosive data resulting from dispatching demand-side resources is always accompanied by substantial costs for data collection and processing [6]. Thus, Fleckenstein *et al.* [7] propose that the data should not be freely provided. Instead, they suggest that it should be traded between the data aggregators (DAs) and the data service operator (DTSO), as depicted in Fig. 1. The DAs act as the data sellers, while the DTSO serves as the data buyer. They further recommend that the DAs aggregate data from multiple data units (DU) before engaging in data trading, which can yield significant advantages [8]. To effectively incentivize data trading between DAs and the DTSO effectively, various entities such as governments, institutions, and industrial companies offer progressive promotions. First, the Chinese government has proposed the establishment of a data trading mechanism. As essential components of this process, several institutions have been established in cities such as Shanghai [9] and Shenzhen [10]. These institutions play a crucial role in facilitating data trading. Moreover, industrial companies have also played a significant part by introducing specific data valuation methods. China Southern Power Grid has developed the Data Asset Pricing Scheme, which provides essential guidance for electricity data trading. Additionally, Guizhou Electric Power Company has released a guidance document for quantifying the value of electricity data and introduced the first transaction price calculator for electricity data products in China [11].

During the process of electricity data trading, it is crucial for the DTSO to obtain valuable data from DAs. Higher-value data can improve the dispatching of large-scale demand-side resources. For example, data with high timeliness are advantageous for dispatching demand-side resources in real-time markets, and data with high quality can enhance the accuracy of dispatching demand-side resources in the power system. However, assessing the value of data can be challenging due to the inherent characteristics of data. Initially, some researchers explore the data valuation methods for specific entities or regulation scenarios, but these methods have certain limitations. For instance, Wang *et al.* [12] propose the data valuation method for power forecasting of solar power plants. Nevertheless, the value of data is distributed across different DAs. To perform an advanced and comprehensive assessment of data valuation, Fleckenstein *et al.* [7] outline multiple data valuation models, such as market-based models, economic models, and dimensional models. Wang *et al.* [3] present a multi-dimensional approach to data valuation, taking into account data quality as an internal characteristic, application as an external characteristic, and risk as a legal characteristic. Given the diverse entities and scenarios within the power system, the dimensional data valuation models can assess the value of data from different DAs.

To enhance the trading of electricity data of large-scale demand-side resources, we investigate an incentive mechanism that involves a data valuation-aware contract between the DTSO and multiple DAs. First, we develop the data valuation model that considers both data quality and data timeliness. Data quality refers to the consistency between the metered realistic data and the final usage data for each DA. Data timeliness refers to the impact of the reception time on the value of data for each DA. Then, we propose a high-value preferred contract for electricity data trading, which combines the trading volume and the reward. In this contract, the DA with high-value data is incentivized to trade more data with the DTSO, and in return, the DTSO provides more rewards to the DA as feedback. Through this approach, the incentive mechanism aims to enhance the value of traded data while optimizing the utility of the DTSO in the data trading process.

The remainder of this paper is organized as follows. Section II establishes the data valuation model and designs the trading contract between DAs and the DTSO. Section III presents the problem formulation. Section IV illustrates the numerical results of case studies. And section V concludes this paper.

II. Contract design

Fig. 2 illustrates the process of data trading involving the DTSO, multiple DAs, and numerous DUs. First, the DA aggregates the data from massive DUs (e.g. smart meters, phase measurement units, et al), equipped for large-scale demand-side resources. Following the aggregation, the data is traded from the DAs to the DTSO based on the trading volume-reward bundled contract. Then, once all traded data is obtained, the DTSO provides data service resources for the application of data in the dispatch of large-scale demand-side resources in the power system.

The DAs possess diverse data sets with varying values, which are determined by their internal characteristics such as

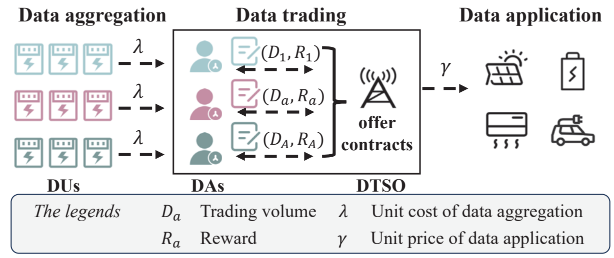


Fig. 2. The data trading process.

data quality and timeliness. Naturally, higher-value data are more inclined to be traded more by the DTSO while lower-value data are expected to be traded less in the trading process. Thus, we propose a data valuation-aware contract between DAs and the DTSO. This contract bundles the trading volume D and the corresponding reward $R(D)$ as a pair $(D, R(D))$. The DA with higher-value data will engage in more data with the DTSO and receive more rewards from the DTSO, while the DA with lower-value data will trade less data and receive fewer rewards. It is noted that the main goal for the DTSO in the proposed mechanism is to acquire data by trading with DAs, which may include various types of data segments.

A. Data valuation modeling

Generally, data quality and data timeliness are the primary factors that determine the value. Besides, the privacy requirements from DAs' data for the trading process may influence the trading dynamics. If DA-a demands a low level of privacy for its data in this trading mechanism, the DTSO will give priority to trading with DA-a as it requires less effort to ensure privacy. Thus, we establish the following data valuation model:

$$\theta_a = (k_a^{\mathrm{Q}}\beta_a^{\mathrm{Q}} + k_a^{\mathrm{T}}\beta_a^{\mathrm{T}})/\tau_a, \quad \forall a \in \mathcal{A}, \tag{1}$$

where θ_a is DA a's data value. It is the weighted average of data quality factor β_a^{Q} and data timeliness factor β_a^{T}. The coefficients k_a^{Q} are k_a^{T} are the weight of the data quality factor and data timeliness factor, respectively, satisfying $k_a^{\mathrm{Q}}+k_a^{\mathrm{T}} = 1$. The symbol $\mathcal{A}$ indicates the set of DAs. The coefficient τ_a represents the privacy requirement of DA-a for the trading process, referring to the level of effort that the DTSO should exert in handling DAs' data. The basic level of privacy requirement is one, i.e., $\tau_a \geq 1$.

1) Data quality factor modeling: The data valuation chain involves numerous components, including the generation of data by distinct units, collection by metering devices, and transmission by communication networks. The process incorporating numerous elements may induce the degradation in data quality between the inherent precision data set prior to the chain and the final collection data set subsequent to the chain. Thus, we define the data quality factor as the consistency between these two data sets. The data quality improves as the consistency increases [13]. In this paper, each DA is associated with two data sets, i.e. the inherent precision data set $\mathcal{Q}_a^{\mathrm{L}}$ and the final collection data set $\mathcal{Q}_a^{\mathrm{R}}$. The disparity between these two data sets results in inconsistency, which is represented by the deviation data set $\mathcal{Q}_a$.

$$q_a = q_a^{\mathrm{L}} - q_a^{\mathrm{R}},\quad \forall q_a \in \mathcal{Q}_a,\ q_a^{\mathrm{L}} \in \mathcal{Q}_a^{\mathrm{L}},\ q_a^{\mathrm{R}} \in \mathcal{Q}_a^{\mathrm{R}},\ \forall a \in \mathcal{A}. \tag{2}$$

It is assumed that the deviation data q_a of DA a follow a normal distribution. The mean and standard deviation of the deviation data are μ_a and σ_a, respectively. Then, the data quality factor β_a^{Q} is modeled as the probability E of the consistency of the data within a certain threshold Q_a^{B}, which is derived by:

$$\beta_a^{\mathrm{Q}} = E(Q_a^{\mathrm{B}}),\quad E(Q_a^{\mathrm{B}}) = \frac{1}{\sqrt{2\pi}\sigma_a}\int_{-Q_a^{\mathrm{B}}}^{Q_a^{\mathrm{B}}} e^{\frac{-(q-\mu_a)^2}{2\sigma_a^2}} dq_a,\quad \forall a \in \mathcal{A}, \tag{3}$$

where q_a is the integral variable. The threshold Q_a^{B} is the maximum permitted deviation of DA a during the data trading process.

2) Data timeliness factor modeling: The value of data will be deduced over the reception time t_a^{rec}. Thus, the data timeliness factor can be derived as:

$$\beta_a^{\mathrm{T}} = (1 - E(Q_a^{\mathrm{B}}))^{t_a^{\mathrm{rec}}/\kappa},\quad \forall a \in \mathcal{A}, \tag{4}$$

where $E(Q_a^{\mathrm{B}})$ is involved in β_a^{T} to directly decide the attenuation rate. And κ is a coefficient of time stretching parameter.

B. DA modeling

When considering the data trading with A DAs, the DAs can be categorized into A types based on the varying value of their data. The data value types of DAs satisfy the following:

$$\theta_1 \le \cdots \le \theta_a \le \cdots \le \theta_A,\quad \forall a \in \mathcal{A}. \tag{5}$$

To accommodate the diverse DAs, the DTSO designs a contract $\mathcal{C} = \{D, R(D)\}$, which is composed of multiple pairs (D_a, R_a) for each data value type. If the DA with data value type a selects the contract (D_a, R_a), it will provide the data volume specified by D_a and receive the reward of R_a. Its utility function can be expressed as:

$$U_a^{\mathrm{DA}}(D_a, R_a) = E_a\tau(R_a) - \lambda D_a,\quad \forall a \in \mathcal{A},\quad \forall a \in \mathcal{A}, \tag{6}$$

where E_a is the effective holding volume of the DA with data value type a, satisfying $E_a = \theta_a H_a$. The product $E_a\tau(R_a)$ is the reward evaluation function of the DA when it receives the reward R_a. And the function $\tau(R_a)$ meets $\tau(R_a)' > 0$ and $\tau(R_a)'' < 0$. The parameter λ indicates the unit cost of data aggregation in Fig. 2. The parameter H_a is the holding data volume of the DA with data value type a, which are available for trading. The symbol $\mathcal{A}$ represents the set of DAs.

C. *DTSO* modeling

When the DA with data value type a selects the contract (D_a, R_a), the DTSO will receive the data of D_a and pay the rewards of R_a. The corresponding utility can be expressed as:

$$U_a^{\mathrm{DTSO}} = \gamma D_a - R_a,\quad \forall a \in \mathcal{A}, \tag{7}$$

where γ indicates the unit price of data application for the DTSO in Fig. 2.

Since the data trading is involved with A DAs, the utility function of the DTSO can be expressed as:

$$U^{\mathrm{DTSO}} = \sum_{a=1}^{A}(\gamma D_a - R_a),\quad \forall a \in \mathcal{A}. \tag{8}$$

III. Problem Formulation

A. Contract constraints

1) Individual rationality (IR) constraints: Involved in the data trading, each DA is an individual rational entity. They will select the contract which ensures the non-negative utility. The constraints can be expressed as follows:

$$U_a^{\mathrm{DA}}(D_a, R_a) = E_a\tau(R_a) - \lambda D_a \ge 0,\quad \forall a \in \mathcal{A}. \tag{9}$$

2) Incentive compatibility (IC) constraints: In the data trading process, the DTSO designs a specific contract for the corresponding DA based on the expected data value type. For example, the contract (D_a, R_a) is designed for the DA with data value type a while the contract (D_b, R_b) is for the DA with data value type b. It follows that the DA is expected to select the default contract rather than any other contract, which can be satisfied by the IC constraints:

$$U_a^{\mathrm{DA}}(D_a, R_a) \ge U_a^{\mathrm{DA}}(D_b, R_b),\quad \forall a, b \in \mathcal{A},\ a \ne b,\quad U_a^{\mathrm{DA}}(D_b, R_b) = E_a\tau(R_b) - \lambda D_b, \tag{10}$$

where $U_a^{\mathrm{DA}}(D_b, R_b)$ is the utility of the data value type a DA selecting the contract (D_b, R_b) for DA b. That means for the data value type a DA ($a \in \mathcal{A}$), the utility contributed by the contract (D_a, R_a) will be no more than that if it chooses any other contract.

3) Monotonicity constraints: The monotonicity in the contract indicates that the DA with a higher data value type will get more rewards from the DTSO, which is derived by:

$$0 \le R_1 \le \cdots \le R_a \le \cdots \le R_N,\quad \forall a \in \mathcal{A}. \tag{11}$$

Furthermore, the DA with higher data value is inclined to sell more data. The monotonicity of the data trading volume D_a can be expressed as follows:

$$0 \le D_1 \le \cdots \le D_a \le \cdots \le D_N,\quad \forall a \in \mathcal{A}. \tag{12}$$

4) Trading limitation constraints: The trading volume D_a is constrained by:

$$D_a \le E_a,\quad \forall a \in \mathcal{A}. \tag{13}$$

B. Optimal contract

The objective function is to maximize the utility of the DTSO. Therefore, the optimization problem in the data trading framework is formulated as follows:

$$\mathbf{P1}:\quad \max\ U^{\mathrm{DTSO}},\quad s.t.:\quad (9) - (13). \tag{14}$$

The number of IR and IC constraints can be reduced from A and $A(A-1)$ in **P1** to 1 and A, respectively [14]. The reduced IR constraint is derived by:

$$E_a\tau(R_1) - \lambda D_1 \ge 0. \tag{15}$$

The reduced IC constraints are derived by:

$$E_a\tau(R_a) - \lambda D_a \ge E_a\tau(R_{a-1}) - \lambda D_{a-1},\quad \forall a \in \mathcal{A},\ a \ne 1. \tag{16}$$

The simplified optimization problem **P2** is formulated by:

$$\textbf{P2}: \quad \max\ U^{\text{DTSO}}, \quad s.t.: (11)-(13), (15)-(16). \tag{17}$$

C. The solving algorithm

The optimization problem **P2** is a concave function by calculating the Hessian matrix. However, the convex optimization method is not applicable for **P2** due to that the reduced IC constraints are the difference between two concave functions. To solve this problem, we introduce the Convex-concave procedure (CCP) algorithm in [15] to transform the reduced IC constraints.

First, we define the reward evaluation function $\phi_a = E_a\tau(R_a)$. Expanded by first-order Taylor series, the reduced IC constraints can be approximately transformed to:

$$\begin{aligned}&\theta_a H_a \tau(R_a^v) - \lambda D_a^v \\ &\geq \phi_a(R_{a-1,0}^v) + \nabla\phi_a(R_{a-1,0}^v)(R_{a-1} - R_{a,0}^v) - \lambda D_{a-1},\end{aligned} \tag{18}$$

where v is the iteration time. The symbol $R_{a,0}^v$ indicates the initial point for Taylor expansion at the v-th iteration, satisfying $R_{a,0}^v = R_a^{v-1}$.

In this paper, we assume $\tau(R_a) = -bR_a^2/2 + cR_a$. Thus, the transformed constraints can be further derived by:

$$\begin{aligned}&\theta_a H_a(-b(R_a^v)^2/2 + cR_a^v) - \lambda D_a^v \\ &\geq \theta_a H_a(b(R_{a-1,0}^v)^2/2 + (c - bR_{a-1,0}^v)R_{a-1}^v) - \lambda D_{a-1}^v.\end{aligned} \tag{19}$$

Thus, the problem **P2** can be solved by the convex optimization method. As described in Algorithm 1, we can find the optimal solutions $\hat{R_a^v}$, $\hat{D_a^v}$ in v-th iteration. The solutions in v-th iteration will be defined as the initial point of the expansion by the Taylor series. Then, the iteration process will stop till the difference of the utilities of the DTSO in the adjacent iterations is less than the given threshold ϵ:

$$|U^{\text{DTSO}}(\{\hat{R_a^v}\}, \{\hat{D_a^v}\}) - U^{\text{DTSO}}(\{\hat{R_a^{v-1}}\}, \{\hat{D_a^{v-1}}\})| \leq \epsilon. \tag{20}$$

Algorithm 1 The CCP-based Solving Algorithm

Input: deviation data sets Q_a, the reception time $t_a^{\text{rec}}, \forall a \in \mathcal{A}$.
Output: optimal $\hat{R}_a$, $\hat{D}_a$

compute DA a's data value $VoD_a, \forall a \in \mathcal{A}$.
initial $v = 0$, the initial reward $\{R_{a,0}^0, \forall a \in \mathcal{A}\}$, and the initial trading volume $\{D_{a,0}^0, \forall a \in \mathcal{A}\}$.
repeat
  approximately transform the reward evaluation $\phi_a(R_a^v)$ into a first-order Taylor expansion.
  transform IC constraints into the affine function and the concave function.
  find optimal solutions $\hat{R_a^v}, \hat{D_a^v}$.
  update: $v = v + 1$, $R_a^{v+1} = \hat{R_a^v}$, $D_a^{v+1} = \hat{D_a^v}$.
until $|U^{\text{DTSO}}(\{\hat{R_a^v}\}, \{\hat{D_a^v}\}) - U^{\text{DTSO}}(\{\hat{R_a^{v-1}}\}, \{\hat{D_a^{v-1}}\})| \leq \epsilon$.

D. Mechanism properties

According to the Impossibility Theorem of Hurwicz, there is no mechanism simultaneously satisfying trading efficiency, individual rationality, incentive compatibility, and budget balance. In the proposed mechanism, trading efficiency is guaranteed as the CCP algorithm ensures the optimality of the trading contract. Individual rationality is guaranteed in Eq. (9) because no DA would select the contract that may result in the trading loss. Incentive compatibility is ensured in Eq. (10) as each DA desires to select the trading contract that yields higher utilities. However, due to the Impossibility Theorem of Hurwicz [16], the proposed mechanism may not achieve budget balance, which comes from the difference between the utility of data application and the costs of data aggregation.

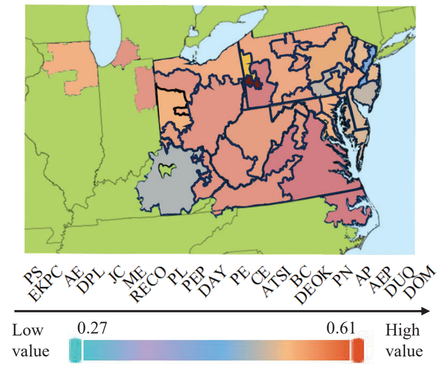


Fig. 3. The distributed data valuation results among 20 DAs.

IV. Case Studies

In this section, we study the data trading mechanism for the local meter load data (Q^{L}) and the remotely transmitted load data (Q^{R}) between DAs and the DTSO.

A. Diverse data values among DAs

To conduct the data valuation, we consider the deviation data sets from 20 DAs. The deviation data comes from public data of 20 transmission zones in PJM on July 10th, 2023 [17], [18]. The reception time parameters are referred to [19].

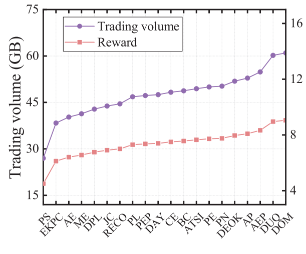
Fig. 3 shows the varying value of data across 20 DAs in the PJM area. The data values are diverse among 20 DAs due to the various data quality and different reception time. For instance, the DOM holds the most valuable data to participate in the data trading while the PS holds the least valuable data.

B. The incentive mechanism for data trading

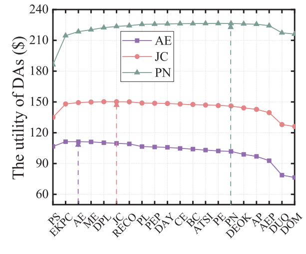
To validate the effectiveness of the proposed data trading mechanism, we consider two cases as follows: **M1**: In the retail mechanism, each DA obtains the reward for the data trading volume from the DTSO at a fixed rate. **M2**: In the proposed mechanism, each DA obtains the different reward for the different data trading volume from the DTSO.

The unit cost of data aggregation λ is 8 \$/GB and the unit price of data application γ is 15 \$/GB. Besides, the holding data volume of each DA H_a is assumed to be the same, and $H_a = 100GB$. All DAs process basic privacy requirements.

1) The contract property: Fig. 4(a) illustrates the data trading contract, i.e., the trading volume and reward, for the DAs with diverse data values in the incentive mechanism. The data from the DAs with higher data value bear more significance compared to those from the DAs with lower data value, particularly owing to superior data quality or reduced reception time. Therefore, the DA with higher-value data trades more data with the DTSO and receives more reward from the DTSO. Consequently, the designed contract can

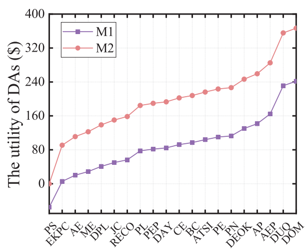


(a) Trading volume and reward

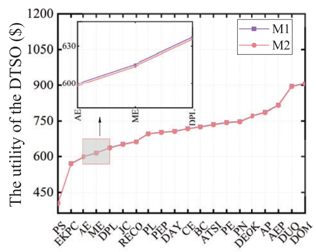


(b) The utility of DAs

Fig. 4. The data trading contract in the proposed incentive mechanism.



(a) The utility of DAs



(b) The utility of DTSO

Fig. 5. The effectiveness of the proposed incentive mechanism.

incentivize the DA with high-value data to actively engage in data trading.

The DTSO provides 20 contracts for 20 DAs in this data trading. Fig. 4(b) shows the utility of each DA when it selects each contract separately. We select three examples of DA's utilities (AE as data value type 3, JC as data value type 6, and PN as data value type 15), as the DA selects each contract from the DTSO. It is evident that each DA consistently selects the proper contract for its data value type with the intention of attaining the optimal utility. For instance, the utility of AE with the data value type of θ_3 is the greatest when it selects the contract intended for data value type 3.

2) The effectiveness of the proposed incentive mechanism: We compare the utility of DAs and the DTSO in the M1 and M2 to verify the effectiveness of the proposed scheme. Fig. 5(a) presents the utility of 20 DAs with varying value of data in M1 and M2, respectively. It can be observed that the DA with higher-value data can achieve greater utility in both M1 and M2. Evidently, the enhanced utility motivates the DA with higher-value data to participate in the data trading.

Fig. 5(b) presents the utility of the DTSO in M1 and M2, respectively. The utility of the DTSO in M1 bears close resemblance to that in M2, while the utility of DAs in M1 is considerably less than that in M2. Although the DTSO will attain marginally more utility in M1 than that in M2, the utility of DAs will be reduced tremendously. Especially for PS (data value type 1), it may fail to trade with the DTSO due to the negative utility in M1. This failure may enormously depress the participation of DAs. In comparison, M2 can effectively incentivize the data trading between DAs and the DTSO.

V. Conclusion

In this paper, we design a data valuation-aware contract as an incentive mechanism for electricity data trading. First, we develop the data valuation model considering both data quality and timeliness. Then, based on the differential data value of DAs, we design a trading volume-reward bundled contract. The DA with higher-value data trades more data with the DTSO and achieves more utility as the motivation. Compared with the fixed retail rate mechanism, the proposed incentive mechanism can effectively motivate valuable data trading. This paper gives an initial exploration on how privacy considerations for data can impact trading dynamics from the prospective of the DTSO. In the future work, we will conduct a more comprehensive analysis to evaluate the potential impact of privacy on data trading, providing a deeper exploration and further discussion.

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