IDADET: Iterative Double-Sided Auction-Based Data-Energy Transaction Ecosystem in Internet of Vehicles

Yang Xu, *Member, IEEE*, Honggang He, *Graduate Student Member, IEEE*, Jia Liu, *Member, IEEE*, Yulong Shen, *Member, IEEE*, Tarik Taleb, *Senior Member, IEEE*, and Norio Shiratori, *Life Fellow, IEEE*

***Abstract*—In the era of big data, the unprecedented growth of data has been regarded as an important asset and the commercial application of data acquisition markets has emerged accordingly. With the advancement of vehicle manufacturing and sensor technologies, a large amount of data can be collected and stored in electric vehicles (EVs), making the data acquisition scenario gradually extend to the Internet of Vehicles (IoV), and thus the corresponding operational rules and economic feasibility need to be fully investigated there. In this article, we focus on a general IoV-oriented data acquisition market that consists of a data center, multiple EVs, multiple roadside units (RSUs), and a market operator (broker), with the objective of social welfare maximization (SWM) by identifying the optimal data task allocation. However, due to the inherent information asymmetry and fragmentation in such a market, it is not feasible to solve the SWM problem directly. To this end, we propose an iterative double-sided auction (IDA) mechanism, which leverages the self-interested feature of RSUs and EVs to decompose the SWM problem, enabling every participant to make decisions in a distributed manner under the broker's coordination. A complete set of operational rules covering the data task allocation, bidding, payment, and reimbursement are elaborately designed to achieve SWM, and energy is adopted as the pricing "currency," such that an IDA-based data-energy transaction (IDADET) ecosystem is established in IoV. We verify the economic feasibility of the proposed IDADET ecosystem by showing its convergence and desirable properties of individual rationality, budget balance, incentive compatibility, and economic efficiency. In addition, considering the psychological effects of practical market participants, we make amendments to the operational rules of the IDADET ecosystem from the behavioral economics perspective, aiming to ensure its long-term well functioning. Extensive numerical results are presented to show the performance of the IDADET ecosystem and demonstrate its advantages in terms of economic properties, operational feasibility, fast convergence, and market social welfare.**

***Index Terms*—Behavioral economics, data-energy transaction, double-sided auction, Internet of Vehicles (IoV), social welfare maximization (SWM).**

I. Introduction

THE RAPID development of the Internet of Things (IoT) has led to the upgrade of traditional vehicular ad hoc networks to the Internet of Vehicles (IoV) [1], [2], [3]. IoV is considered to carry tremendous research value and commercial interest, and thereby attracting increasing attention from both academic and industrial communities [4], [5]. With the advancement of vehicle manufacturing and sensor technologies, vehicles in IoV are equipped with various sensors with computing and storing capabilities, and are, therefore, able to collect and store extensive data. Meanwhile, with the assistance of 5G/B5G communications and cloud computing, large-scale IoT data transmission can be easily realized. In this context, massive data contained in IoV are regarded as an important asset, and the data acquisition there has become an emerging business model that benefits commercial entities and creates new revenue streams for Internet enterprises [6].

On the one hand, as more and more sensors are equipped in modern vehicles, the amount of data generated from monitoring both the on-road and in-vehicle status is significantly rising. This explosive growth of generated vehicular data, along with the increasing data demands from data platforms and users, has resulted in a tremendous potential for data transactions in IoV [7]. On the other hand, due to real-time changes in the geographic location, moving vehicles can implement data transactions with multiple participating entities while driving, such as vehicle-to-vehicle, vehicle-to-roadside unit (RSU), and vehicle-to-agent [8], [9]. As a result, there is an urgent need to establish a data acquisition market with well-refined operational procedures and rules that enable massive and efficient data transactions in IoV.

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Yang Xu and Yulong Shen are with the School of Computer Science and Technology, Xidian University, Xi'an 710071, China (e-mail: yxu@xidian.edu.cn; ylshen@mail.xidian.edu.cn).

Honggang He is with the School of Economics and Management, Xidian University, Xi'an 710071, China (e-mail: hghe@stu.xidian.edu.cn).

Jia Liu is with the School of Computer Science and Technology, Xidian University, Xi'an 710071, China, and also with the Center for Strategic Cyber Resilience Research and Development, National Institute of Informatics, Tokyo 101-8430, Japan (e-mail: jliu@nii.ac.jp).

Tarik Taleb is with the Center for Wireless Communications, Faculty of Information Technology and Electrical Engineering, University of Oulu, 90570 Oulu, Finland (e-mail: tarik.taleb@oulu.fi).

Norio Shiratori is with the Research and Development Initiative, Chuo University, Tokyo 112-8551, Japan (e-mail: norio@riec.tohoku.ac.jp).

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By now, some preliminary works have been done to explore the development of data acquisition markets and the design of data transaction mechanisms. For instance, Yu et al. [10] introduced a brokerage-based market, in which participants propose their selling and buying quantities to the trading platform that matches the market supply and demand, and developed a prospect theory model from behavioral economics to analyze the users' realistic trading behaviors. Liu et al. [11] proposed a blockchain-enhanced data market framework to support secure and efficient IoT data trading and formulated a two-stage Stackelberg game to solve the pricing and purchasing problem between the data consumer and the market agency. Lin et al. [12] developed a consortium blockchain for secure and efficient knowledge management and trading and applied the noncooperative game to design a knowledge pricing strategy with incentives for the market. Nguyen et al. [13] proposed a benchmarking framework for evaluating data trading protocols and analyzed the communication efficiency of three basic IoT data trading protocols via NB-IoT connectivity in terms of latency and energy consumption.

A. Motivation and Contributions

Although the above existing works represent brilliant progress in the study of data acquisition markets, they are not dedicatedly designed for and, therefore, do not match well IoV. In particular, information asymmetry is a key feature of data markets in IoV, that is, a market participant cannot fully know others' information, such as willingness and utilities. Therefore, under the insufficient and asymmetric market information, how to design the operational procedures for a data acquisition market in IoV as well as the operational rules to regulate the behaviors of market participants, is a great challenge and remains largely uninvestigated. Meanwhile, to realize the practical commercialization of the proposed data acquisition market in IoV, its economic feasibility must also be fully demonstrated.

Motivated by the above statements, in this article, we explore the design of a general data acquisition market oriented toward IoV, in which mobile vehicles roaming in a wide area gather data by equipped sensors, and randomly deployed RSUs work as data exchange stations to acquire data from passing vehicles and then deliver data to a data center over base stations. Our goal is to achieve social welfare maximization (SWM) for the data acquisition market in IoV under the information asymmetry constraint. To this end, we develop an iterative double-sided auction (IDA) mechanism, which is able to encourage market participants to gradually report their truthful information and incentivizes vehicles to exchange data by issuing reimbursements. Note that along with the global trend of low-carbon living, alternative fuel vehicles, especially, electric vehicles (EVs), are becoming mainstream in the automotive market [14], and electrical energy is the most essential resource for EVs. Hence, we consider the IoV composed of EVs and use energy as the reimbursements for EVs to perform data acquisition tasks, thus, establishing an IDA-based data-energy transaction (IDADET) ecosystem in IoV. Moreover, we conduct theoretical analyses for the economic feasibility of the proposed ecosystem and make amendments to the operational rules according to market participants' psychological behaviors.

In summary, this article makes the following contributions.

1) *Novel IoV-Oriented Data-Energy Transaction Ecosystem Design:* To the best of our knowledge, for the emerging IoV and the potentially huge data assets therein, this work is the first to develop a novel data energy transaction ecosystem with the goal of maximizing total social welfare, named IDADET. To cope with the market information asymmetry, we apply the idea of IDA to design the transaction mechanism, which enables RSUs and EVs to make decisions in a distributed manner under a broker's coordination. Correspondingly, a complete set of operational rules are elaborately formulated to regulate entities' interactions, including data allocation, bidding, and pricing. Therefore, this work can be considered a new and appropriate application of IDA in an emerging area, and the comparative results indicate that the IDA mechanism does have advantages in terms of convergence and social welfare.
2) *Economic Feasibility Analysis:* We show the convergence of the IDA mechanism by proving it converges to the unique solution to the market SWM problem. We also prove the IDADET ecosystem satisfies the desirable economic properties of individual rationality (IR), incentive compatibility (IC), economic efficiency (EE), and budget balance (BB). These theoretical analyses demonstrate the economic feasibility of the IDADET ecosystem in IoV.
3) *Behavioral Economics-Based Amendment:* We further consider the phenomenon that the psychological behaviors of participants have effects on the data acquisition market, which may occur in the real world. Accordingly, we make amendments to the operational rules of the IDADET ecosystem from the behavioral economics perspective. We identify appropriate additional energy reimbursements that grant to EVs to compensate for their psychological loss during continuous data collection task implementation, so as to guarantee the long-term well-functioning of the IDADET ecosystem.

B. Paper Organization

The remainder of this article is organized as follows. We introduce related work in Section II. Section III describes the system model and problem formulation. The IDADET ecosystem is established in Section IV. We verify the economic feasibility of the IDADET ecosystem in Section V and make amendments to the IDA mechanism from the behavioral economics perspective in Section VI. Section VII presents the numerical results, followed by the conclusion in Section VIII.

II. Related Work

Data have become an important asset in the current era of big data. Many existing studies have demonstrated the feasibility of data transaction implementation, based on which the issues, such as data transaction mechanism design and data transaction pricing, have been widely investigated [15]. In recent years, IoT provides a class of typical application scenarios for data transactions and has been attracting increasing academic attention [16], [17], [18], [19]. Specially, Jung et al. [16] investigated the responsibilities of consumers in the data set trading and designed a set of accountable protocols to secure the big data transaction environment, achieving book-keeping ability and accountability against dishonest consumers with misbehaviors. Taking into account the characteristics of data consumers and data providers as well as the conflict between data privacy and data exploitation, Oh et al. [17] applied the noncooperative game model to develop a competitive data transaction scheme with privacy valuation for multiple stakeholders in IoT data markets. Zheng et al. [18] proposed a profit-driven data acquisition framework for crowd-sensed data markets, which is composed of two complementary mechanisms for profit maximization and for payment minimization, respectively. The architecture design problem of the mobile crowd-sensed data market was investigated in [19], where a reward sharing scheme was developed to incentivize data providers to contribute data according to some fairness criteria, and an online query-based data pricing mechanism was designed to determine the trading price of crowd-sensed data and guarantee both arbitrage-freeness and a constant competitive ratio in terms of profit maximization.

More recently, by formulating the interactions between the mobile operator and users in the data trading market as a three-stage Stackelberg game, Yu et al. [20] studied the users' operator selection and trading decisions and analyzed the operator's profit-maximizing strategy. In [21], a framework for data trading over the Internet of artificially intelligent things was established, where the security and pricing issues were investigated, and a data trading strategy was proposed to jointly maintain the model performance and the budget consumption. Zhang et al. [22] proposed a smart contract-based quality-driven incentive mechanism for secure data sharing among IoT devices with limited resources, where a two-layer Stackelberg game of nested coalitional scheme was designed to realize the maximum overall social welfare. By designing a two-phase sampling-based algorithm and two types of pricing strategies for different data trading circumstances, Cai et al. [23] studied the range counting trading for IoT data with the objective of preserving the privacy of data contributors. The problem of trustworthy data sharing in two-stage industrial IoTs was investigated in [24], where two scenarios were considered based on the availability of prior knowledge on devices, and three device allocation algorithms were designed to guarantee the total scales of data per round while achieving the fairness among devices and system owners.

Since blockchain technology has been gradually contributing to the improvement of data transaction markets, some works exploring blockchain-based data trading in IoT can be found in the literature. For example, with the help of the smart contract technique, Zhao et al. [25] proposed a blockchain-based fair data trading protocol for the big data market, which combines ring signature, double-authentication-preventing signature, and similarity learning to guarantee the availability of trading data, the privacy of data providers, and fairness between data providers and consumers. To mitigate limitations in conventional data trading markets with dishonest buyers/data brokers, Dai et al. [26] established a new blockchain-based ecosystem, by introducing a paradigm shift where a buyer obtains the result of the data analysis rather than the actual data set, using blockchain to allow the tracing of unauthorized transactional modifications, and building a secure contract execution environment to protect the source data and the analysis result. In [27], based on the blockchain technology, a privacy-preserving incentive private data sharing scheme was constructed for IoT, to realize the behavior profile-building prevention and nonframeability and ensure the flexible access control of multisharing. Liu et al. [28] developed a transparent data marketing architecture with the cloud as a data management unit and the consortium blockchain as a reliable controller, which achieves consortium management and executable fairness in the cloud-based marketing model with a distributed committee.

With the advancement of wireless communications and sensor technologies, a large amount of data is collected and stored in EVs, which makes the data transaction scenario gradually extend to the context of the IoV. The commodity value of data will bring new value attributes to EVs, and, therefore, the data transaction in IoV has become a new research focus in recent years. Liu et al. [9] used the blockchain technology to propose a secure and decentralized data transaction system and designed a debit–credit mechanism to support efficient data trading in IoV, where a two-stage Stackelberg game was formulated to maximize the profits of borrowing and lending vehicles jointly. Lu et al. [29] developed a federated learning-based data-sharing architecture to relieve transmission load and address privacy concerns of providers in IoV, where a hybrid model consisting of the permissioned blockchain and the local directed acyclic graph is used to enhance security and reliability, and an asynchronous federated learning scheme for node selection was proposed to improve efficiency. Sadiq et al. [30] adopted consortium blockchain to maintain transparency and trust in data and energy trading activities in IoV, where smart contracts were utilized to tackle trading disputes and illegal actions, and an elliptic curve bilinear pairing-based digital signature scheme was developed to ensure data reliability and integrity. Chai et al. [31] proposed a hierarchical blockchain-enabled federated learning algorithm for knowledge sharing in large-scale IoV, where the knowledge sharing was modeled as a trading market process to stimulate sharing behaviors, and the hierarchical federated learning algorithm is designed to meet the distributed pattern and privacy requirement of IoV. Zou et al. [32] developed a regional federated learning framework for knowledge trading in IoV, where a reputation mechanism was designed to measure the reliability of participating vehicles, and a blockchain-enhanced trading scheme along with a noncooperative game-based pricing strategy was proposed to ensure an authorized market agency coordinates the trading quickly.

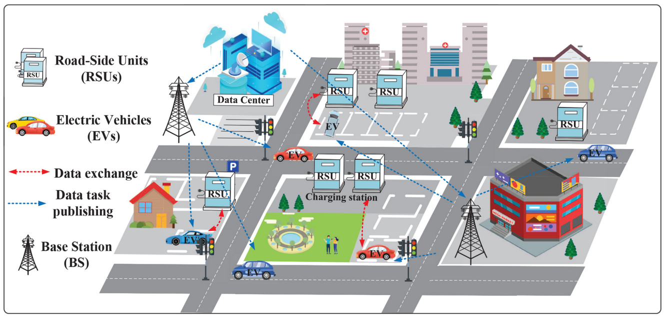

Fig. 1. IoV-oriented data acquisition market.

It is worth noting that this work is distinguishable from the existing ones in the sense that we fully consider the information asymmetry in the practical IoV-oriented data acquisition market, and elaborately design an IDA mechanism with a complete set of operational rules covering the resource allocation, bidding, payment, and reimbursement, so as to establish a data-energy transaction ecosystem in IoV with provable decent economic properties. In addition, we investigate the psychological effects of market participants from the behavioral economics perspective and make amendments to the operational rules to achieve the long-term well-functioning of the data-energy transaction ecosystem.

III. System Model and Problem Formulation

In this section, we first introduce the system model of the IoV-oriented data acquisition market, and then formulate the SWM problem with the consideration of both EVs and RSUs.

A. IoV-Oriented Data Acquisition Market

As illustrated in Fig. 1, we consider a data acquisition market in a wide-area IoV, which is composed of a data center, multiple RSUs, and multiple EVs. Base stations serve as the information infrastructure to provide wide-area data communication services. Let $\mathcal{M} = \{1, \ldots, M\}$ and $\mathcal{N} = \{1, \ldots, N\}$ denote the sets of RSUs and EVs, respectively, where M and N are the numbers of RSUs and EVs in the IoV. With the help of base stations, the data center can release a series of data collection tasks to RSUs and EVs in a broadcasting way. Each EV roaming in the wide-area IoV gathers data from the sensors carried in itself and extracts valid data to meet the data collection task demands. RSUs are deployed randomly in different regions of the IoV, which work as data exchange stations to acquire data from passing EVs in a way of D2D communications by adopting short-range wireless communication technologies. Then, RSUs deliver data to the data center over the information infrastructure provided by the base stations.

For a data collection task undertaken by RSU $m \in \mathcal{M}$, let $x_{m,n}$ denote the percentage of data that RSU m expects to receive from EV $n \in \mathcal{N}$, and $y_{n,m}$ denote the percentage of data that EV n is willing to offer RSU m. Then, the data request matrix of the whole market, denoted by $\boldsymbol{X}$, is expressed as

$$\boldsymbol{X} \triangleq (\boldsymbol{x}_m \ \forall m \in \mathcal{M}) = \left(x_{m,n} \ \forall m \in \mathcal{M} \ \forall n \in \mathcal{N}\right) \tag{1}$$

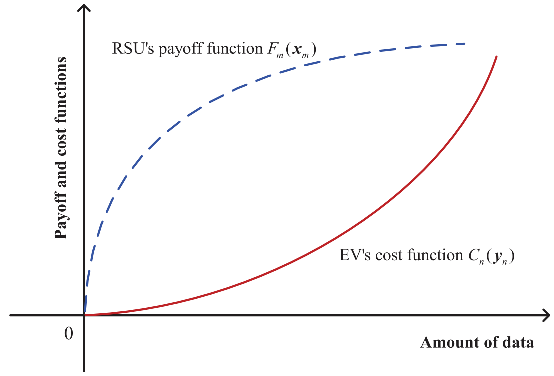

Fig. 2. Trends of RSU's payoff function and EV's cost function.

and the data offer matrix of the whole market, denoted by $\boldsymbol{Y}$, is expressed as

$$\boldsymbol{Y} \triangleq \left(\boldsymbol{y}_n \ \forall n \in \mathcal{N}\right) = \left(y_{n,m} \ \forall n \in \mathcal{N} \ \forall m \in \mathcal{M}\right). \tag{2}$$

Let $F_m(\boldsymbol{x}_m)$ denote the payoff function of RSU m by acquiring data vector $\boldsymbol{x}_m$ from EVs. Obviously, $F_m(\boldsymbol{x}_m)$ is a positive and increasing function of the data request vector $\boldsymbol{x}_m$ and satisfies $F_m(\mathbf{0}) = 0$, in accordance with the fact that the more data acquired, the more benefits can be achieved. In addition, note that "diminishing marginal returns" is a generic economic law reflecting the phenomenon that the benefits from gaining an item when there is nothing are greater than the benefits from gaining the same item when there are already a lot of possessions. To make the payoff function conform to the law of diminishing marginal returns, $F_m(\boldsymbol{x}_m)$ should be strictly concave in $\boldsymbol{x}_m$. On the other hand, implementing data collection tasks will cost EVs in terms of power, computing resources, and so on. Let $C_n(\boldsymbol{y}_n)$ denote the cost function of EV n by offering data vector $\boldsymbol{y}_n$ to RSUs, which is positive, increasing, and satisfies $C_n(\mathbf{0}) = 0$. Moreover, we assume the cost function conforms to the generic economic law of "increasing marginal costs" and, thus, $C_n(\boldsymbol{y}_n)$ is strictly convex in $\boldsymbol{y}_n$, which captures the fact that as the offered data by an EV increases, its operation cost for gathering one more unit of data increases, since the EV has to roam a wider area for gathering data, and meanwhile there are fewer remaining resources for extracting and maintaining valid data. Fig. 2 shows the trends of payoff function $F_m(\boldsymbol{x}_m)$ of RSU m and cost function $C_n(\boldsymbol{y}_n)$ of EV n.

Remark 1: The economic laws of diminishing marginal returns and increasing marginal costs are commonly applied in data trading markets, for example, [12], [17]. Note that, here, we only stipulate these two economic laws for the payment function and cost function, without restricting the specific function expressions, which indicates that the ecosystem and scheme developed in the work are universally applicable. In the simulations, we will specify the expressions of the payoff function and cost function as case studies. As introduced later, our objective is to maximize the social welfare of the whole market, which is the difference between the total payoffs and the total costs. The assumption of diminishing marginal returns and increasing marginal costs implies that a worst-case is considered, and, thus, the proposed solution can guarantee an achievable lower bound for the market social welfare.

B. Problem Formulation

Clearly, the objectives of RSUs and EVs are intrinsically conflicting with each other. On the one hand, RSUs expect to obtain as much data as possible to achieve a higher payoff. On the other hand, EVs tend to collect less data to save their cost. If they decide unilaterally how much data to request and to offer, it is impossible to reach an agreement. To this end, there is a need for a market operator, who works as a broker to help coordinate the interactions among RSUs and EVs, ensuring that the market operates efficiently.

In the IoV-oriented data acquisition market, social welfare is the aggregate utility of all involved entities and, thus, represents the market's operational efficiency. Specifically, let $S(\boldsymbol{X}, \boldsymbol{Y})$ denote the social welfare, which is the difference between the total payoff of RSUs and the total cost of EVs, given by

$$S(\boldsymbol{X}, \boldsymbol{Y}) = \sum_{m=1}^{M} F_m(\boldsymbol{x}_m) - \sum_{n=1}^{N} C_n(\boldsymbol{y}_n). \tag{3}$$

To improve the market's operational efficiency, the broker needs to undertake the task of maximizing social welfare by negotiating appropriate data request matrix $\boldsymbol{X}$ and data offer matrix $\boldsymbol{Y}$. Thus, the SWM problem for the broker can be formulated as

$$\text{SWM:} \quad \max_{\boldsymbol{X},\boldsymbol{Y}} S(\boldsymbol{X}, \boldsymbol{Y}) = \sum_{m=1}^{M} F_m(\boldsymbol{x}_m) - \sum_{n=1}^{N} C_n(\boldsymbol{y}_n) \tag{4a}$$

$$\text{s.t.} \quad \sum_{m=1}^{M} y_{n,m} \leq 1 \ \forall n \in \mathcal{N} \tag{4b}$$

$$x_{m,n} \leq y_{n,m} \ \forall n \in \mathcal{N} \ \forall m \in \mathcal{M} \tag{4c}$$

$$y_{n,m} \geq 0, \ x_{m,n} \geq 0 \ \forall n \in \mathcal{N} \ \forall m \in \mathcal{M} \tag{4d}$$

where (4c) indicates that the data amount supplied by each EV should satisfy the corresponding data amount requested by the RSU. Note that the objective function of the SWM problem is strictly concave and the constraint set is compact and convex. Hence, the SWM problem admits a unique optimal solution that can be characterized by using the necessary and sufficient Karush–Kuhn–Tucker (KKT) conditions.

Specifically, we relax (4b) and (4c) and define the Lagrangian function of the SWM problem as follows:

$$\begin{aligned}\mathcal{L}_1(\boldsymbol{\lambda}, \boldsymbol{\mu}, \boldsymbol{X}, \boldsymbol{Y}) = &\sum_{m=1}^{M} F_m(\boldsymbol{x}_m) - \sum_{n=1}^{N} C_n(\boldsymbol{y}_n) \\ &- \sum_{n=1}^{N} \lambda_n \left(\sum_{m=1}^{M} y_{n,m} - 1 \right) \\ &- \sum_{m=1}^{M} \sum_{n=1}^{N} \mu_{m,n} (x_{m,n} - y_{n,m})\end{aligned} \tag{5}$$

where $\boldsymbol{\lambda} \triangleq (\lambda_n \geq 0 \ \forall n \in \mathcal{N})$ is the Lagrange multiplier vector corresponding to constraints (4b), and $\boldsymbol{\mu} \triangleq (\mu_{m,n} \geq 0 \ \forall m \in \mathcal{M} \ \forall n \in \mathcal{N})$ is the Lagrange multiplier matrix corresponding to constraints (4c). Then, the KKT conditions of the SWM problem that yield the optimal primal variables $\boldsymbol{X}^*$ and $\boldsymbol{Y}^*$ and the optimal dual variables $\boldsymbol{\lambda}^*$ and $\boldsymbol{\mu}^*$ are given by the following set of equations:

$$\frac{\partial F_m(\boldsymbol{x}_m^*)}{\partial x_{m,n}^*} - \mu_{m,n}^* = 0 \tag{6a}$$

$$\frac{\partial C_n(\boldsymbol{y}_n^*)}{y_{n,m}^*} - (\mu_{m,n}^* - \lambda_n^*) = 0 \tag{6b}$$

$$\sum_{n=1}^{N} \lambda_n^* \left(\sum_{m=1}^{M} y_{n,m}^* - 1 \right) = 0 \tag{6c}$$

$$\sum_{m=1}^{M} \sum_{n=1}^{N} \mu_{m,n}^* (x_{m,n}^* - y_{n,m}^*) = 0 \tag{6d}$$

$$\lambda_n^* \geq 0, \ \mu_{m,n}^* \geq 0, \ x_{m,n}^* \geq 0, \ y_{n,m}^* \geq 0. \tag{6e}$$

According to (6a) and (6b), the optimal solutions of $x_{m,n}$ and $y_{n,m}$ satisfy

$$\begin{cases} \dfrac{\partial F_m(x_{m,n}^*)}{\partial x_{m,n}^*} = \mu_{m,n}^* & \text{(7a)} \\[2ex] \dfrac{\partial C_n(y_{n,m}^*)}{y_{n,m}^*} = (\mu_{m,n}^* - \lambda_n^*). & \text{(7b)} \end{cases}$$

However, it is infeasible for the broker to derive the optimal solution to the SWM problem by solving (6a)–(6e) directly, due to the information asymmetry in the IoV-oriented data acquisition market. Specifically, the RSU payoff function set $\{F_m(\boldsymbol{x}_m) \ \forall m \in \mathcal{M}\}$ and the EV cost function set $\{C_n(\boldsymbol{y}_n) \ \forall n \in \mathcal{N}\}$ are local information for RSUs and EVs, respectively, and the broker cannot be aware of such information. To eliminate this lack of information, it is necessary to design an incentive mechanism for the broker to encourage RSUs and EVs to report their truthful data request amount and data offer amount, respectively.

IV. IDA-Based Data-Energy Transaction Ecosystem Design

In this section, we design an IDA mechanism to solve the SWM problem in the IoV-oriented data acquisition market, which is a powerful measure to deal with information asymmetry. The basic principle of IDA is to leverage the self-interested feature of RSUs and EVs and decompose the original market operation problem such that RSUs and EVs can make decisions in a distributed manner under the broker's mild coordination. Specifically, the broker solves an alternative optimization problem to determine $\boldsymbol{X}$ and $\boldsymbol{Y}$ (called *allocation rule*), which is combined with appropriate *pricing rules* (i.e., payments for RSUs and reimbursements for EVs) so as to achieve the optimal solution to the original SWM problem. This mechanism corresponds to a double-sided auction facilitated by the broker, where multiple buyers (RSUs) and multiple sellers (EVs) interact in an iterative manner to adjust their bids until the market reaches an optimal and feasible point. Note that in IoV scenarios, energy is the most essential resource for EVs and the function of energy supply can be integrated into RSUs. Therefore, we adopt energy as the "currency" of payments and reimbursements in the IDA mechanism, establishing a data-energy transaction ecosystem in IoV. In the following, we elaborate on the allocation rule, the optimal pricing rules, and the implementation of the IDADET ecosystem, sequentially.

A. Allocation Rule

The IDA mechanism comprises the following two steps in each iteration.

Step I: Each RSU $m \in \mathcal{M}$ submits a bid $u_{m,n} \geq 0$ for each EV $n \in \mathcal{N}$ to the broker, implying the data it expects to exchange. Similarly, each EV $n \in \mathcal{N}$ submits a bid $v_{m,n} \geq 0$ for each RSU $m \in \mathcal{M}$ to the broker, which reflects its cost for collecting data. We define the bid vector $\boldsymbol{u}_m$ for RSU m and the bid vector $\boldsymbol{v}_n$ for EV n as follows:

$$\boldsymbol{u}_m \triangleq \left(u_{m,n}\ \forall n \in \mathcal{N}\right) \tag{8}$$

$$\boldsymbol{v}_n \triangleq \left(v_{n,m}\ \forall m \in \mathcal{M}\right). \tag{9}$$

The bids will be utilized as the inputs during the allocation procedure at Stage II, and to further determine the actual payments of RSUs and reimbursements of EVs.

Step II: By following the previous studies on network utility maximization, e.g., [33] and [34], we employ a logarithmic function along with a quadratic function to design the allocation rule, which can capture the concave and convex increasing properties of the RSU's payoff function and the EV's cost function, respectively. Specifically, after receiving the bid vectors $(\boldsymbol{u}_m\ \forall m \in \mathcal{M})$ and $(\boldsymbol{v}_n\ \forall n \in \mathcal{N})$ from both sides, the broker determines the data request/offer matrices by solving the following broker's allocation (BA) problem:

$$\text{BA:} \quad \max_{\boldsymbol{X},\boldsymbol{Y}} \sum_{m=1}^{M}\sum_{n=1}^{N}\left(u_{m,n}\ln x_{m,n} - \frac{1}{2}v_{n,m}y_{n,m}^2\right) \tag{10a}$$

$$\text{s.t.} \quad \sum_{m=1}^{M} y_{n,m} \leq 1\ \forall n \in \mathcal{N} \tag{10b}$$

$$x_{m,n} \leq y_{n,m}\ \forall n \in \mathcal{N}\ \forall m \in \mathcal{M} \tag{10c}$$

$$y_{n,m} \geq 0,\ x_{m,n} \geq 0\ \forall n \in \mathcal{N}\ \forall m \in \mathcal{M}. \tag{10d}$$

Note that the BA problem possesses the same constraint set as the SWM problem but has a different yet strictly concave objective function, so it admits a unique optimal solution. Then, we define the corresponding Lagrange function of the BA problem as

$$\begin{aligned}\mathcal{L}_2(\boldsymbol{\lambda},\boldsymbol{\mu},\boldsymbol{X},\boldsymbol{Y}) = &\sum_{m=1}^{M}\sum_{n=1}^{N}\left(u_{m,n}\ln x_{m,n} - \frac{1}{2}v_{n,m}y_{n,m}^2\right)\\ &-\sum_{n=1}^{N}\lambda_n\left(\sum_{m=1}^{M}y_{n,m}-1\right)\\ &-\sum_{m=1}^{M}\sum_{n=1}^{N}\mu_{m,n}\left(x_{m,n}-y_{n,m}\right).\end{aligned} \tag{11}$$

The KKT conditions that yield the optimal primal variables $\boldsymbol{X}^\dagger$ and $\boldsymbol{Y}^\dagger$ and the optimal dual variables $\boldsymbol{\lambda}^\dagger$ and $\boldsymbol{\mu}^\dagger$ are given by the following set of equations:

$$\frac{u_{m,n}}{x_{m,n}^\dagger} - \mu_{m,n}^\dagger = 0 \tag{12a}$$

$$v_{n,m}\cdot y_{n,m}^\dagger - \left(\mu_{m,n}^\dagger - \lambda_n^\dagger\right) = 0 \tag{12b}$$

$$\sum_{n=1}^{N}\lambda_n^\dagger\left(\sum_{m=1}^{M}y_{n,m}^\dagger - 1\right) = 0 \tag{12c}$$

$$\sum_{m=1}^{M}\sum_{n=1}^{N}\mu_{m,n}^\dagger\left(x_{m,n}^\dagger - y_{n,m}^\dagger\right) = 0 \tag{12d}$$

$$\lambda_n^\dagger \geq 0,\ \mu_{m,n}^\dagger \geq 0,\ x_{m,n}^\dagger \geq 0,\ y_{n,m}^\dagger \geq 0. \tag{12e}$$

According to conditions in (12a) and (12b), we have the allocation rules for two sides as

$$\begin{cases} x_{m,n}^\dagger = \dfrac{u_{m,n}}{\mu_{m,n}^\dagger} & \text{(13a)}\\[2ex] y_{n,m}^\dagger = \dfrac{\mu_{m,n}^\dagger - \lambda_n^\dagger}{v_{n,m}}. & \text{(13b)}\end{cases}$$

B. Optimal Pricing Rules

Comparing the KKT conditions (6a)–(6e) with (12a)–(12e), we can note that the BA problem has the same optimal solution as the SWM problem, i.e., $\boldsymbol{X}^\dagger = \boldsymbol{X}^*$ and $\boldsymbol{Y}^\dagger = \boldsymbol{Y}^*$, if the submitted bids from RSUs and EVs satisfy the following equations:

$$\begin{cases} u_{m,n} = x_{m,n}^\dagger \dfrac{\partial F_m(\boldsymbol{x}_m^\dagger)}{\partial x_{m,n}^\dagger} & \text{(14a)}\\[2ex] v_{n,m} = \dfrac{1}{y_{n,m}^\dagger}\dfrac{\partial C_n(\boldsymbol{y}_n^\dagger)}{\partial y_{n,m}^\dagger}. & \text{(14b)}\end{cases}$$

In consequence, the broker should design appropriate pricing rules, i.e., the payment rule for RSUs and the reimbursement rule for EVs, which are capable of inducing RSUs and EVs to submit bids following expressions (14a) and (14b), respectively.

We first investigate the behavior of RSUs as bidders. Let $P_m(\boldsymbol{x}_m)$ denote the payments required to be paid by RSU m to the broker if RSU m receives data $\boldsymbol{x}_m$ from EVs. It is worth noting that in the IDA mechanism, the data vector $\boldsymbol{x}_m$ is not requested by RSU m directly, but is determined based on the bid from RSU m as well as the allocation rule (13a). The payment rule $P_m(\boldsymbol{x}_m)$ is carried out by the broker and each RSU only needs to find its optimal bid vector $\boldsymbol{u}_m$ to maximize its own utility, i.e., payoff minus payments. Specifically, each RSU m solves the following RSU's utility maximization (RUM) problem:

$$\text{RUM:} \quad \max_{\boldsymbol{u}_m}\ F_m(\boldsymbol{x}_m) - P_m(\boldsymbol{x}_m) \tag{15a}$$

$$\text{s.t.} \quad u_{m,n} \geq 0\ \forall n \in \mathcal{N}. \tag{15b}$$

By setting the first-order derivative of the objective function (15a) with respect to $u_{m,n}$ to be 0 and applying the allocation rule (13a), we can derive that the optimal solution of the RUM problem satisfies

$$\frac{\partial P_m(\boldsymbol{x}_m)}{\partial u_{m,n}} = \frac{\partial F_m(\boldsymbol{x}_m)}{\partial x_{m,n}} \cdot \frac{\partial x_{m,n}}{\partial u_{m,n}} = \frac{\partial F_m(\boldsymbol{x}_m)}{\partial x_{m,n}} \cdot \frac{1}{\mu^{\dagger}_{m,n}}. \quad (16)$$

Moreover, to achieve the maximal social welfare, RSU m should submit the bid according to (14a). Then, by substituting (14a) into (16) we have

$$\frac{\partial P_m(\boldsymbol{x}_m)}{\partial u_{m,n}} = \frac{1}{\mu^{\dagger}_{m,n}} \cdot \frac{u_{m,n}}{x_{m,n}} = 1. \quad (17)$$

Therefore, the payment rule that requires RSU m to pay the broker is determined as

$$P_m(\boldsymbol{u}_m) = \sum_{n=1}^{N} u_{m,n}. \quad (18)$$

We next check the behavior of EVs as bidders. Let $Q_n(\boldsymbol{y}_n)$ denote the reimbursements provided by the broker to EV n if EV n exchanges data vector $\boldsymbol{y}_n$ to RSUs. Similarly, here, the data vector $\boldsymbol{y}_n$ is determined based on the bid from EV n and the allocation rule (13b). The reimbursement rule $Q_n(\boldsymbol{y}_n)$ is implemented by the broker and each EV only needs to find its optimal bid vector $\boldsymbol{v}_n$ to maximize its own utility, i.e., reimbursements minus cost. Specifically, each EV n solves the following EV's utility maximization (EUM) problem:

$$\text{EUM:} \quad \max_{\boldsymbol{v}_n} \; Q_n(\boldsymbol{y}_n) - C_n(\boldsymbol{y}_n) \quad (19a)$$

$$\text{s.t.} \quad v_{n,m} \geq 0 \; \forall m \in \mathcal{M}. \quad (19b)$$

By setting the first-order derivative of the objective function (19a) with respect to $v_{n,m}$ to be 0 and applying the allocation rule (13b), we can derive that the optimal solution of the EUM problem satisfies

$$\frac{\partial Q_n(\boldsymbol{y}_n)}{\partial v_{n,m}} = \frac{\partial C_n(\boldsymbol{y}_n)}{\partial y_{n,m}} \cdot \frac{\partial y_{n,m}}{\partial v_{n,m}} = -\frac{\partial C_n(\boldsymbol{y}_n)}{\partial y_{n,m}} \cdot \frac{\mu^{\dagger}_{m,n} - \lambda^{\dagger}_n}{(v_{n,m})^2}. \quad (20)$$

To achieve the maximal social welfare, EV n should submits the bid according to (14b). Then, by substituting (14b) into (20) we have

$$\frac{\partial Q_n(\boldsymbol{y}_n)}{\partial v_{n,m}} = -v_{n,m} y_{n,m} \frac{\mu^{\dagger}_{m,n} - \lambda^{\dagger}_n}{(v_{n,m})^2} = -\frac{\left(\mu^{\dagger}_{m,n} - \lambda^{\dagger}_n\right)^2}{(v_{n,m})^2}. \quad (21)$$

Therefore, the reimbursement rule that requires the broker to pay EV n is given by

$$Q_n(\boldsymbol{v}_n) = \sum_{m=1}^{M} \frac{\left(\mu^{\dagger}_{m,n} - \lambda^{\dagger}_n\right)^2}{v_{n,m}} = \sum_{m=1}^{M} y_{n,m}\left(\mu^{\dagger}_{m,n} - \lambda^{\dagger}_n\right). \quad (22)$$

C. Implementation of IDA-Based Data-Energy Transaction Ecosystem

By applying the allocation rules (13a), (13b) as well as the payment rule (18) and the reimbursement rule (22), the RSUs and EVs can calculate their optimal bids and the broker can achieve the market equilibrium for SWM in one round, *if* they know the complete market information including RSUs' payoff functions and EVs' cost functions. However, due to the information asymmetry, an iterative algorithm is required to gradually adjust the market operation point to converge to the desirable one.

Algorithm 1 IDA Mechanism

Initialization:

Initialize $\boldsymbol{X}^{(0)}$, $\boldsymbol{Y}^{(0)}$, $\boldsymbol{\lambda}^{(0)}$, $\boldsymbol{\mu}^{(0)}$;

Set parameters $t = 0$, flag $= 0$, $\delta, \epsilon_1, \epsilon_2 > 0$;

while flag $= 0$ **do**

  $t = t + 1$;

  Broker: announces $\boldsymbol{\lambda}^{(t-1)}$ and $\boldsymbol{\mu}^{(t-1)}$;

  Each RSU: finds the optimal bid $\boldsymbol{u}^{(t)}_m$ by solving the RUM problem and submits it to the broker;

  Each EV: finds the optimal bid $\boldsymbol{v}^{(t)}_n$ by solving the EUM problem and submits it to the broker;

  Broker: decides the data allocation $\boldsymbol{X}^{(t)}$ and $\boldsymbol{Y}^{(t)}$ according to

$$x^{(t)}_{m,n} = \frac{u^{(t)}_{m,n}}{\mu^{(t-1)}_{m,n}}, \quad y^{(t)}_{n,m} = \frac{\mu^{(t-1)}_{m,n} - \lambda^{(t-1)}_n}{v^{(t)}_{n,m}};$$

  Broker: updates $\boldsymbol{\lambda}^{(t)}$ and $\boldsymbol{\mu}^{(t)}$ according to

$$\lambda^{(t)}_n = \max\left\{\lambda^{(t-1)}_n + \delta\left(\sum_{m=1}^{M} y^{(t)}_{n,m} - 1\right), 0\right\};$$

$$\mu^{(t)}_{m,n} = \max\left\{\mu^{(t-1)}_{m,n} + \delta\left(x^{(t)}_{m,n} - y^{(t)}_{n,m}\right), 0\right\};$$

  Broker: checks convergence

  if $\left|\frac{u^{(t)}_{m,n} - u^{(t-1)}_{m,n}}{u^{(t-1)}_{m,n}}\right| < \epsilon_1$ and $\left|\frac{v^{(t)}_{n,m} - v^{(t-1)}_{n,m}}{v^{(t-1)}_{n,m}}\right| < \epsilon_2$ **then**

    flag=1;

    Determines the payments and reimbursements as

$$P_m(\boldsymbol{u}^{(t)}_m) = \sum_{n=1}^{N} u^{(t)}_{m,n};$$

$$Q_n(\boldsymbol{v}^{(t)}_n) = \sum_{m=1}^{M} y^{(t)}_{n,m}(\mu^{(t)}_{m,n} - \lambda^{(t)}_n);$$

  end if

end while

Output:

Optimal data allocation: $\boldsymbol{X}^{(t)}, \boldsymbol{Y}^{(t)}$;

Optimal payments for RSUs and reimbursements for EVs: $P_m(\boldsymbol{u}^{(t)}_m)$, $Q_n(\boldsymbol{v}^{(t)}_n)$;

The procedures of the IDA mechanism can be described as follows. At the beginning of each iteration, the broker announces the up-to-date dual variables, i.e., the Lagrange multiplies $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$. Then, each RSU and each EV determine their optimal bids by solving the RUM and EUM problems, respectively, and submit the bids to the broker. After receiving

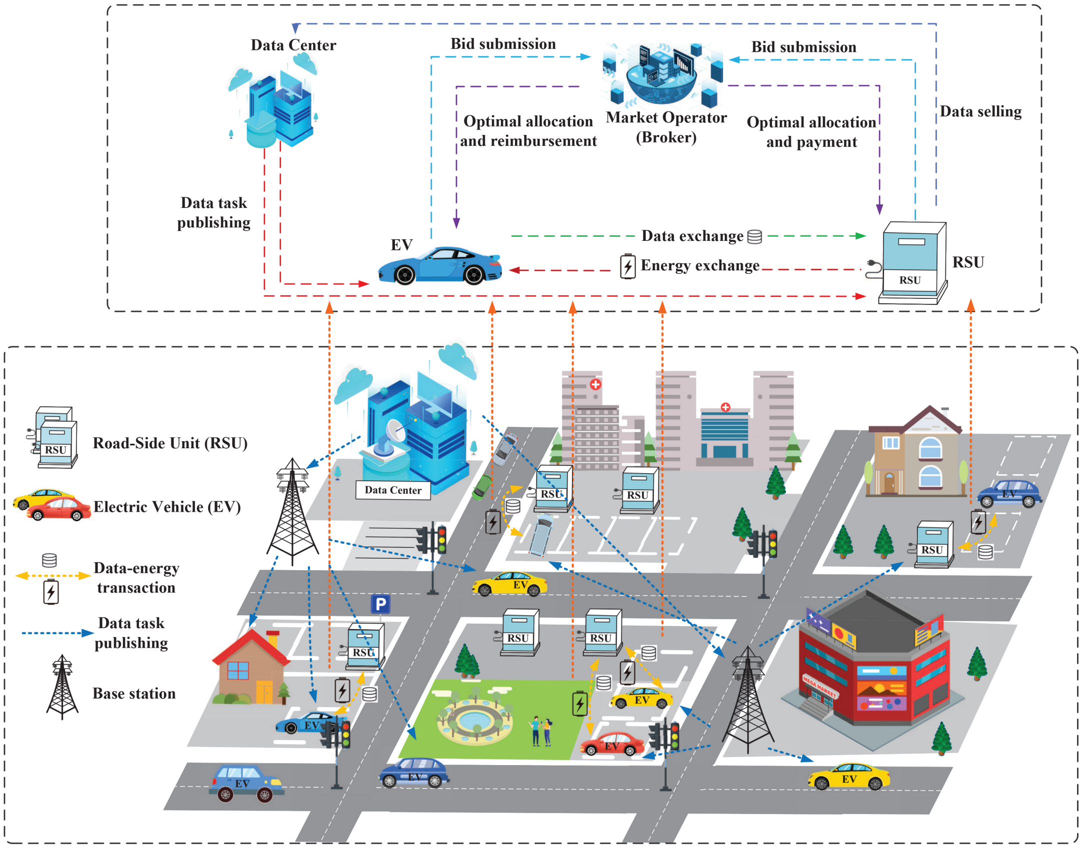

Fig. 3. IDADET ecosystem.

the bids, the broker decides the current optimal allocation and pricing by solving the BA problem, which produces the new data matrices $\boldsymbol{X}$ and $\boldsymbol{Y}$ as well as the Lagrange multipliers $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$. Note that the RUM and EUM problems are parameterized by the Lagrange multipliers of the BA problem, in turn, the BA problem is parameterized by the bids of the RUM and EUM problems, that is the reason they need to be solved iteratively based on the feedback from the market. In particular, for the BA problem, we make use of its decomposable structure and adopt the primal–dual Lagrangian decomposition approach [34], [35] to solve it. As a result, the broker updates the dual variables $\boldsymbol{\lambda}$ and $\boldsymbol{\mu}$ in a gradient descent way as follows:

$$\begin{aligned}\lambda_n^{(t+1)} &= \max\left\{\lambda_n^{(t)} - \delta \cdot \frac{\partial \mathcal{L}_2}{\partial \lambda_n}, 0\right\}\\ &= \max\left\{\lambda_n^{(t)} + \delta\left(\sum_{m=1}^{M} y_{n,m} - 1\right), 0\right\} \quad \forall n \in \mathcal{N} \qquad (23)\end{aligned}$$

$$\begin{aligned}\mu_{m,n}^{(t+1)} &= \max\left\{\mu_{m,n}^{(t)} - \delta \cdot \frac{\partial \mathcal{L}_2}{\partial \mu_{m,n}}, 0\right\}\\ &= \max\left\{\mu_{m,n}^{(t)} + \delta\left(x_{m,n} - y_{n,m}\right), 0\right\}\\ &\qquad \forall n \in \mathcal{N}\ \forall m \in \mathcal{M} \qquad (24)\end{aligned}$$

where $\delta > 0$ is the step size and t represents the iteration index. Then, the broker checks whether the current bids reach stability. If not, the above procedures are repeated until the bids reach stability, which indicates the market reaches equilibrium. The details of the IDA mechanism are summarized in Algorithm 1.

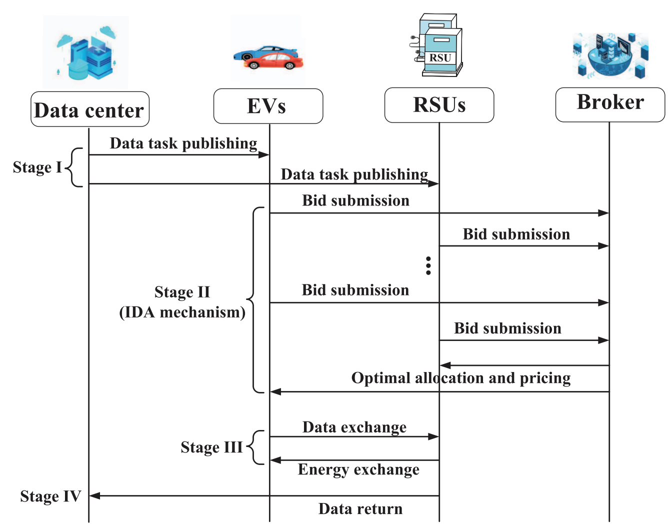

Fig. 4. Operation process of IDADET ecosystem.

As mentioned previously, since energy is essential for EVs and the function of energy supply can be integrated into RSUs, we use energy as payments for RSUs and reimbursements for EVs in the IDA mechanism. Consequently, we establish an IDADET ecosystem in IoV, with a complete architecture as illustrated in Fig. 3 and a whole operation process as shown in Fig. 4. In the IDADET ecosystem, the data center publishes data acquisition tasks to RSUs and EVs. Then, EVs aggregate data and will exchange data to RSUs for energy. A broker (market operator) is engaged in this stage to facilitate the data-energy transaction process between EVs and RSUs, who executes the IDA mechanism (Algorithm 1) to regulate and induce the market behaviors of buyers and sellers. According to the data allocation and pricing decided by the broker, EVs and RSUs implement the data and energy exchange. Finally, RSUs return the data purchased from EVs to the data center. The proposed IDADET ecosystem possesses a set of desirable properties such that RSUs and EVs are willing to participate in it, resulting in virtuous and sustainable operations. In the next section, we will introduce and prove these properties sequentially.

Remark 2: Regarding the practical implementation and commercialization of the IDADET ecosystem, except for the proposed IDA transaction mechanism, the underlying technologies in terms of wireless communications and energy transfer are also significant. As mentioned in the system model, the information infrastructure consisting of base stations (which have been already widely used in human life for a long time) can help broadcast the data collection tasks and deliver the data from RSUs to the data center. When adjacent RSUs and EVs conduct transactions, data can be transmitted in a way of D2D communications by using short-range wireless communication technologies, while energy reimbursements can be achieved by wireless charging. The details of various technical implementations of wireless charging can be found in [36].

V. Economic Feasibility of IDADET Ecosystem

In this section, we verify the economic feasibility of the proposed IDADET ecosystem. We first analyze the convergence of the IDA mechanism and then prove the desirable economic properties of the ecosystem, including IR, IC, EE, and BB.

A. Convergence of IDA Mechanism

Regarding the convergence of the proposed IDA mechanism, we have the following theorem.

Theorem 1: The IDA mechanism designed for the data-energy transaction between RSUs and EVs converges to the unique optimal solution to the SWM problem formulated in (4a)–(4d).

Proof: According to the update functions (23) and (24), the dynamics of the dual variables λ_n and $\mu_{m,n}$, defined as $\dot{\lambda}_n(t) = \lambda_n^{(t+1)} - \lambda_n^{(t)}$ and $\dot{\mu}_{m,n}(t) = \mu_{m,n}^{(t+1)} - \mu_{m,n}^{(t)}$, are given by

$$\dot{\lambda}_n(t) = \begin{cases} \delta\left(\sum_{m=1}^{M} y_{n,m} - 1\right), & \lambda_n^{(t+1)} > 0 \\ 0, & \lambda_n^{(t+1)} = 0 \end{cases} \tag{25}$$

$$\dot{\mu}_{m,n}(t) = \begin{cases} \delta\left(x_{m,n} - y_{n,m}\right), & \mu_{m,n}^{(t+1)} > 0 \\ 0, & \mu_{m,n}^{(t+1)} = 0. \end{cases} \tag{26}$$

We define the Lyapunov function as

$$V(\boldsymbol{\lambda}, \boldsymbol{\mu}) = \frac{1}{2}\sum_{n=1}^{N}\left(\lambda_n - \lambda_n^{\dagger}\right)^2 + \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(\mu_{m,n} - \mu_{m,n}^{\dagger}\right)^2. \tag{27}$$

Let $\dot{V}(\boldsymbol{\lambda}, \boldsymbol{\mu})$ denote the first-order derivative of the Lyapunov function with respect to t, which satisfies inequality (28), shown at the bottom of the page. From the KKT conditions, we have $([\partial F_m(\boldsymbol{x}_m^{\dagger})]/[\partial x_{m,n}^{\dagger}]) = \mu_{m,n}^{\dagger}$ and $([\partial C_n(\boldsymbol{y}_n^{\dagger})]/[\partial y_{n,m}^{\dagger}]) = \mu_{m,n}^{\dagger} - \lambda_n^{\dagger}$. Then, inequality (28) can be transformed to (29), shown at the bottom of the page.

Due to the strictly concave property of RSUs' payoff functions and the strictly convex property of EVs' cost functions, we have

$$\begin{aligned} &\left(\frac{\partial F_m(\boldsymbol{x}_m)}{\partial \boldsymbol{x}_m} - \frac{\partial F_m(\boldsymbol{x}_m^{\dagger})}{\partial \boldsymbol{x}_m}\right)\left(x_{m,n} - x_{m,n}^{\dagger}\right) \le 0 \\ &\left(\frac{\partial C_n(\boldsymbol{y}_n)}{\partial \boldsymbol{y}_n} - \frac{\partial C_n(\boldsymbol{y}_n^{\dagger})}{\partial \boldsymbol{y}_n}\right)\left(y_{n,m} - y_{n,m}^{\dagger}\right) \le 0. \end{aligned} \tag{30}$$

$$\begin{aligned} \frac{\dot{V}(\boldsymbol{\lambda}, \boldsymbol{\mu})}{\delta} &\triangleq \frac{\mathrm{d}V(\boldsymbol{\lambda}, \boldsymbol{\mu})}{\delta \cdot \mathrm{d}t} = \sum_{n=1}^{N}\left(\lambda_n - \lambda_i^{\dagger}\right)\hat{\lambda}_n(t) + \sum_{m=1}^{M}\sum_{n=1}^{N}\left(\mu_{m,n} - \mu_{m,n}^{\dagger}\right)\hat{\mu}_{m,n}(t) \\ &\le \sum_{n=1}^{N}\left(\lambda_n - \lambda_n^{\dagger}\right)\left(\sum_{m=1}^{M} y_{n,m} - 1\right) + \sum_{m=1}^{M}\sum_{n=1}^{N}\left(\mu_{m,n} - \mu_{m,n}^{\dagger}\right)\left(x_{m,n} - y_{n,m}\right) \\ &= \sum_{n=1}^{N}\left(\lambda_n - \lambda_n^{\dagger}\right)\left(\sum_{m=1}^{M} y_{n,m} - \sum_{m=1}^{M} y_{n,m}^{\dagger}\right) + \sum_{n=1}^{N}\left(\lambda_n - \lambda_n^{\dagger}\right)\left(\sum_{m=1}^{M} y_{n,m}^{\dagger} - 1\right) + \sum_{m=1}^{M}\sum_{n=1}^{N}\left(\mu_{m,n} - \mu_{m,n}^{\dagger}\right)\left(x_{m,n}^{\dagger} - y_{n,m}^{\dagger}\right) \\ &\quad + \sum_{m=1}^{M}\sum_{n=1}^{N}\left(\mu_{m,n} - \mu_{m,n}^{\dagger}\right)\left[\left(x_{m,n} - x_{m,n}^{\dagger}\right) - \left(y_{n,m} - y_{n,m}^{\dagger}\right)\right] \end{aligned} \tag{28}$$

$$\frac{\dot{V}(\boldsymbol{\lambda}, \boldsymbol{\mu})}{\delta} \le \sum_{m=1}^{M}\sum_{n=1}^{N}\left(\frac{\partial F_m(\boldsymbol{x}_m)}{\partial \boldsymbol{x}_m} - \frac{\partial F_m(\boldsymbol{x}_m^{\dagger})}{\partial \boldsymbol{x}_m}\right)\left(x_{m,n} - x_{m,n}^{\dagger}\right) + \sum_{m=1}^{M}\sum_{n=1}^{N}\left(\frac{\partial C_n(\boldsymbol{y}_n)}{\partial \boldsymbol{y}_n} - \frac{\partial C_n(\boldsymbol{y}_n^{\dagger})}{\partial \boldsymbol{y}_n}\right)\left(y_{n,m} - y_{n,m}^{\dagger}\right) \tag{29}$$

Therefore, $\dot{V}(\boldsymbol{\lambda}, \boldsymbol{\mu}) \leq 0$ holds, and according to the Lyapunov stability theory [37], [38], $\lambda_n^{(t)}$ and $\mu_{m,n}^{(t)}$ converge, further indicating that the IDA mechanism converges. In addition, the pricing rules adopted by the IDA mechanism are able to induce RSUs and EVs to submit bids following (14a) and (14b), respectively, ensuring that the outputs converge to the unique optimal solution to the SWM problem. This completes the proof. ∎

B. Economic Properties

The concerned desirable economic properties include IR, BB, IC, and EE, which are defined as follows.

1) *IR:* By participating in the IDADET ecosystem, RSUs and EVs will never obtain negative utilities, i.e., they will be at least not worse than those who do not participate in the ecosystem.
2) *BB:* There is no additional investment required for the market operator (broker) to make the IDADET ecosystem work well. That is, the negotiated payments from each RSU to the broker is no less than the reimbursements from the broker to the corresponding EV.
3) *IC:* Both sides of the auction, i.e., RSUs and EVs, are incentivized to reveal their local information truthfully.
4) *EE:* The IDADET ecosystem is able to realize the SWM.

Theorem 2: The proposed IDADET ecosystem possesses the desirable economic properties of IR, BB, IC, and EE.

In what follows, we prove these economic properties sequentially.

1) IR:

Proof: Since $F_m(\boldsymbol{x}_m)$ is a strictly concave function of $\boldsymbol{x}_m$ and $F_m(\mathbf{0}) = 0$, according to the Lagrange's mean value theorem, we have

$$F_m\left(\boldsymbol{x}_m^{\dagger}\right) \geq F_m(\mathbf{0}) + x_{m,n}^{\dagger}\frac{\partial F_m\left(\boldsymbol{x}_m^{\dagger}\right)}{\partial x_{m,n}^{\dagger}} = x_{m,n}^{\dagger}\frac{\partial F_m\left(\boldsymbol{x}_m^{\dagger}\right)}{\partial x_{m,n}^{\dagger}}. \quad (31)$$

Considering the optimal bid and payments of RSU m, there is

$$x_{m,n}^{*}\frac{\partial F_m\left(\boldsymbol{x}_m^{\dagger}\right)}{\partial x_{m,n}^{\dagger}} = x_{m,n}^{\dagger}\frac{u_{m,n}}{x_{m,n}^{\dagger}} = P_m\left(\boldsymbol{u}_m^{\dagger}\right) \quad (32)$$

which implies the following inequalities always hold

$$F_m\left(\boldsymbol{x}_m^{\dagger}\right) \geq P_m\left(\boldsymbol{u}_m^{\dagger}\right) \; \forall m \in \mathcal{M}. \quad (33)$$

Similarly, considering the strictly convex property of EVs' cost function $C_n(\boldsymbol{y}_n)$ as well as the optimal bid and reimbursements of EV n, we can deduce that the following inequalities always hold

$$Q_n\left(\boldsymbol{v}_n^{\dagger}\right) - C_n\left(\boldsymbol{y}_n^{\dagger}\right) \geq 0 \; \forall n \in \mathcal{N}. \quad (34)$$

We have the following conclusions: on the one hand, RSUs and EVs can always gain a non-negative utility by participating in the IDADET ecosystem; on the other hand, they have no gain if they do not participate. Therefore, the designed IDADET ecosystem satisfies the IR property. ∎

2) BB:

Proof: According to the RUM problem of each RSU and the EUM problem of each EV, the budget of the broker, denoted as $\Theta(\boldsymbol{U}, \boldsymbol{V})$, is given by

$$\begin{aligned}\Theta(\boldsymbol{U}, \boldsymbol{V}) &= \sum_{m=1}^{M} P_m(\boldsymbol{u}_m) - \sum_{n=1}^{N} Q_n(\boldsymbol{v}_n)\\ &= \sum_{m=1}^{M}\sum_{n=1}^{N}\left[u_{m,n} - \frac{\left(\mu_{m,n} - \lambda_n\right)^2}{v_{n,m}}\right]\\ &= \sum_{m=1}^{M}\sum_{n=1}^{N}\left[\mu_{m,n}x_{m,n} - y_{n,m}\left(\mu_{m,n} - \lambda_n\right)\right].\end{aligned}$$

When all participants submit their optimal bids, there is

$$\begin{aligned}\Theta\left(\boldsymbol{U}^{\dagger}, \boldsymbol{V}^{\dagger}\right) &= \sum_{m=1}^{M}\sum_{n=1}^{N}\mu_{m,n}^{\dagger}\left(x_{m,n}^{\dagger} - y_{n,m}^{\dagger}\right)\\ &\quad + \sum_{n=1}^{N}\lambda_n^{\dagger}\sum_{m=1}^{M}\sum_{n=1}^{N}\left(y_{n,m}^{\dagger} - 1\right) + \sum_{n=1}^{N}\lambda_n^{\dagger}. \quad (35)\end{aligned}$$

It indicates that when the broker receives the optimal bids $\boldsymbol{u}_m$ and $\boldsymbol{v}_n$ from both sides, due to the KKT constraints, it will always gain a non-negative budget. Therefore, the designed IDADET ecosystem satisfies the BB property. ∎

3) IC:

Proof: According to our derivations, it is clear that RSUs and EVs do not need to report their private information to the broker, but submit their current optimal bids to the broker by locally solving the RUM problem and the EUM problem, respectively. In addition, these iteratively updated optimal bids can gradually reveal RSUs' hidden payoff and EVs' hidden cost. In other words, RSUs and EVs do not share information with the broker, but the optimal bids that they submit will gradually eliminate confidential information and ultimately maximize social welfare. Therefore, the designed IDADET ecosystem satisfies the IC property. ∎

4) EE:

Proof: According to Theorem 1, we can know that the IDA mechanism converges to an optimal solution where the KKT conditions (12a)–(12e) are satisfied. In addition, adopting the pricing rules regulated by (18) and (22) when the broker charges payments from RSUs and provides reimbursements to EVs, respectively, the optimal bids produced by the IDA mechanism can result in the optimal data allocation $\boldsymbol{X}^{\dagger}$ and $\boldsymbol{Y}^{\dagger}$, which are equivalent to the optimal solution of the SWM problem. Therefore, the designed IDADET ecosystem can achieve SWM and satisfies the EE property. ∎

VI. Amendment Based on Behavioral Economics

In real-world economic markets, the psychological and emotional behaviors of economic participants usually have non-negligible impacts on their psychological utilities and decision making. For instance, it is common that the psychological utility of the same food is higher for a hungry person than for an already-full one due to different psychological expectations held by the two types of people. Similarly, in our proposed IDADET ecosystem, if an EV has been participating in data acquisition tasks for a long time but there is never a "salary" (energy reimbursement) raise, its willingness to continue participating may decline, which could eventually lead to the entire ecosystem coming to a halt. Taking into account such effects and aiming to achieve the long-term well-functioning of the IDADET ecosystem, in this section, we make amendments to its operational rules by applying the theory of behavioral economics, which is widely used to explain the extent to which incentives affect participants' psychology [39], [40], [41], [42].

Consider a long-term operation of the IDADET ecosystem going through multiple rounds of data acquisition task releases, let Q_n^r denote the energy reimbursements gained by EV n in the data acquisition task of round r. Similar to [43], we also utilize the concept of participation capital deposits (PCDs), which is defined as follows.

Definition 1 (PCDs): The depreciated sum of energy reimbursements gained by EV n is referred to as its PCDs. Specifically, let Γ_n^r denote the PCD of EV n after accomplishing the rth round of data acquisition task, and then we have

$$\Gamma_n^r = \sum_{m=1}^{M} Q_{n,m}^r + \phi_n \Gamma_n^{r-1} \tag{36}$$

where $Q_{n,m}^r$ denotes the energy reimbursements gained by EV n from RSU m, and $\phi_n \in (0, 1)$ is the depreciation rate of EV n's PCD.

From the perspective of behavioral economics, the depreciation rate measures the degree of decline in the psychological value of past cumulative gains. In this context, to compensate for the psychological loss of EVs during long-term participation (working), we amend the operational rules of the IDADET ecosystem by regulating that EVs should be compensated for additional energy reimbursements during each round of data acquisition task. Let $\chi_{n,m}^r$ denote the additional energy compensation provided by RSU m to EV n at round r. In the following, we analyze the single-round satisfaction and the long-term psychological experience of EVs from the perspective of behavioral economics, which are termed product utility and experience utility, respectively. Based on the analysis of product utility and experience utility, we then determine the additional energy compensation $\chi_{n,m}^r$.

A. Product Utility

In the theory of behavioral economics, the product utility of a participant reflects its satisfaction with the gain in a single round of participation. Let $\Phi_{n,m}^r$ denote the product utility of EV n obtained from RSU m at the rth round of data acquisition task, and it is calculated by the single-round utility of an EV multiplying a corresponding satisfaction rate. Therefore, $\Phi_{n,m}^r$ can be formulated as

$$\Phi_{n,m}^r = \left(Q_{n,m}^r\left(y_{n,m}^r\right) - C_{n,m}^r\left(y_{n,m}^r\right) + \chi_{n,m}^r\right)\rho_{n,m}^r \tag{37}$$

where $\rho_{n,m}^r$ is the satisfaction rate of EV n with RSU m, used to measure the product utility gained from the unit profit.

We consider that there are two factors that affect the satisfaction rate $\rho_{n,m}^r$. On the one hand, $\rho_{n,m}^r$ is related to the ratio of energy reimbursements from RSU m to the total reimbursements from all RSUs. The higher this ratio, the larger the satisfaction rate $\rho_{n,m}^r$. On the other hand, $\rho_{n,m}^r$ is related to the ratio of the total reimbursements to the expected return. The lower this ratio, the larger $\rho_{n,m}^r$, due to the fact that when the reimbursements are scarce compared with the expected return, the unit reimbursement can bring more psychological value. Let R_n^r denote the expected return of EV n in the rth round and combing the above discussions, we formulate the satisfaction rate $\rho_{n,m}^r$ as

$$\rho_{n,m}^r = \sqrt{\frac{Q_{n,m}^r + \chi_{n,m}^r}{\sum_{m=1}^{M}\left(Q_{n,m}^r + \chi_{n,m}^r\right)}} \cdot e^{-\frac{\sum_{m=1}^{M}\left(Q_{n,m}^r + \chi_{n,m}^r\right)}{R_n^r}}. \tag{38}$$

B. Experience Utility

The experience utility describes the long-term psychological experience of EVs participating in data acquisition tasks. Specifically, PCD and the cumulative task cost are two factors to affect the experience utility of an EV. Let B_n^r denote the cost threshold of EV n at the rth round, which is used to capture the EV's sensitivity to the cost of implementing data acquisition tasks. Then, the experience utility of EV n for RSU m up to the rth round of tasks, denoted as $\Psi_{n,m}^r$, is given by

$$\Psi_{n,m}^r = \sqrt{\frac{\alpha_{n,m}\Gamma_n^{r-1}}{\Omega_n^{r-1}}} \cdot e^{-\frac{\sum_{m=1}^{M} C_{n,m}^r\left(y_{n,m}^r\right)}{B_n^r}} \tag{39}$$

where $0 < \alpha_{n,m} < 1$ is a discount factor and Ω_n^{r-1} is the accumulative negative utility.

Unlike PCD, there is no depreciation rate for the accumulative negative utility because the negative utility represents the cost of immediate expenditure and past expenditure does not have a depreciation effect on the current task. Then, we have

$$\Omega_n^r = \omega_n^r + \Omega_n^{r-1} \tag{40}$$

where ω_n^r denotes the negative utility of EV n at the rth round, and it is expressed as

$$\omega_n^r = \sum_{m=1}^{M} C_{n,m}^r\left(y_{n,m}^r\right) \cdot \sigma_{n,m}^r. \tag{41}$$

The cost factor $\sigma_{n,m}^r$ is used to measure the negative utility resulting from the unit cost and it is related to the situation that whether the EV's expect return is achieved. Let $A_n^r = \sum_{m=1}^{M} Q_{n,m}^r + \sum_{m=1}^{M} \chi_{n,m}^r$ denote the current sum-revenue. Before the expected return is achieved, i.e., $A_n^r \leq R_n^r$, EV n pursues meeting the expected return and, therefore, only considers the cost of completing the data collection task for the current RSU. When the expected return is already achieved, i.e., $A_n^r > R_n^r$, EV n conducting data tasks for new RSUs will incur more cost, so a decision needs to be made based on the total cost, whether to continue the task for profit or stop it for cost saving. Therefore, the cost factor $\sigma^r_{n,m}$ is formulated as

$$\sigma^r_{n,m} = \begin{cases} \left(\dfrac{C^r_{n,m}\left(y^r_{n,m}\right)}{\sum_{m=1}^{M}\chi^r_{n,m} - \sum_{m=1}^{M} C^r_{n,m}\left(y^r_{m,n}\right) + B^r_n}\right)^{\frac{R^r_n}{A^r_n}}, & A^r_n \le R^r_n \\ \left(\dfrac{\sum_{m=1}^{M} C^r_n\left(y^r_{n,m}\right)}{\sum_{m=1}^{M}\chi^r_{n,m} - \sum_{m=1}^{M} C^r_{n,m}\left(y^r_{m,n}\right) + B^r_n}\right)^{\frac{R^r_n}{A^r_n}}, & A^r_n > R^r_n. \end{cases} \tag{42}$$

According to the theory of behavioral economics, we define the combined utility Ξ^r_n of EV n as the sum of its product utility and experience utility, which is expressed as

$$\Xi^r_n = \sum_{m=1}^{M}\Phi^r_{n,m} + \sum_{m=1}^{M}\Psi^r_{n,m}. \tag{43}$$

Regarding the combined utility, we have the following theorem.

Theorem 3: If there is no additional energy compensation, i.e., $\chi^r_{n,m} = 0$, although the EV's combined utility increases as it is continuously engaged in the IDA mechanism, the combined utility per task decreases.

Proof: The proof of Theorem 3 is equivalent to proving that as M becomes larger, Ξ^r_n increases but $(\Phi^r_{n,m} + \Psi^r_{n,m})$ decreases. Since $\Phi^r_{n,m} > 0$ and $\Psi^r_{n,m} > 0$, from expression (43), it is obvious that the growth of M leads to an increase in Ξ^r_n. Taking the first-order derivative of $\delta^r_{n,m}$ with respect to M yields

$$\frac{\partial \delta^r_{n,m}}{\partial M} = -\frac{e^{-\frac{\sum_{m=1}^{M} Q^r_{n,m}}{R^r_n}}}{2\cdot M^{\frac{3}{2}}} - \frac{Q^r_{n,m}\sqrt{\frac{1}{M}}\,e^{-\frac{\sum_{m=1}^{M} Q^r_{n,m}}{R^r_n}}}{R^r_n} < 0. \tag{44}$$

Taking the first-order derivative of $\Psi^r_{n,m}$ with respect to M yields

$$\frac{\partial \Psi^r_{n,m}}{\partial M} = -e^{-\frac{\sum_{m=1}^{M} C^r_n\left(y^r_{n,m}\right)}{B^r_n}} \cdot \sqrt{\frac{\alpha_{n,m}\Gamma_n^{r-1}}{\Omega_n^{r-1}}} \cdot \frac{y^r_{n,m}}{B^r_n} < 0. \tag{45}$$

Then, we have $([\partial(\Phi^r_{n,m} + \Psi^r_{n,m})]/\partial M) < 0$, i.e., $(\Phi^r_{n,m} + \Psi^r_{n,m})$ decreases as M increases. This completes the proof. ■

C. Amended IDA Mechanism

According to Theorem 3, we know that if there is no additional energy compensation, the product utility and experience utility gained by an EV from a new data task decreases when this EV continues being engaged in the IDA mechanism for a long time. From the behavioral economics perspective, although the IDA mechanism is able to achieve convergence for each round of data acquisition task, the psychological satisfaction of EVs for the energy exchanged per unit of data will decrease with the growth of the participating period. Over time, this could result in the dropping out of more and more EVs, leading to the eventual shutdown of the IDADET ecosystem.

To relieve EVs' psychological dissatisfaction, it is necessary to introduce additional energy reimbursements. Therefore, we make amendments to the IDA mechanism by providing each EV n with $\sum_{m=1}^{M}\chi^r_{n,m}$ energy reimbursements after the

Algorithm 2 Behavioral Economics-Oriented Amended IDA Mechanism

Initialization:

Initialize ecosystem parameters Γ^1_n, Ω^1_n, R^r_n, B^r_n, set $r = 1$ and maximum round of data acquisition task $r_{\max}$;

while $r < r_{\max}$ **do**
  Data center release r-th round task and IDADET ecosystem performs **Algorithm 1**;
  Calculate satisfaction rate $\rho^r_{n,m}$ according to (38);
  Calculate cost factor $\sigma^r_{n,m}$ according to (42);
  Calculate energy compensation $\chi^r_{n,m}$ according to (46);
  Provide EVs with energy compensation;
  Calculate product utility $\Phi^r_{n,m}$ according to (37);
  Calculate experience utility $\Psi^r_{n,m}$ according to (39);
  $r = r + 1$
end while

Output:

Energy compensation $\chi^r_{n,m}$, product utility $\Phi^r_{n,m}$, and experience utility $\Psi^r_{n,m}$;

double-sided auction converges, such that EVs are motivated to continue participating in the next round of data acquisition tasks. The energy compensation $\chi^r_{n,m}$ should be determined based on the satisfaction rate and cost factor of each round, and, thus, it is formulated as

$$\begin{aligned}\chi^r_{n,m} = {} & \left(1 + \sigma^{r-1}_{n,m}\right) C^{r-1}_n\left(y^{r-1}_{n,m}\right) \\ & + \left(\max\left\{\rho^{r-1}_{n,m}, m \in \mathcal{M}\right\} - \rho^{r-1}_{n,m}\right) Q^{r-1}_{n,m}\left(y^{r-1}_{n,m}\right).\end{aligned} \tag{46}$$

Hence, in Algorithm 2, we summarize the amended IDA mechanism that copes with behavioral economics.

VII. Numerical Results

In this section, we conduct extensive numerical simulations to demonstrate the performance of the IDADET ecosystem. We first show the behaviors of EVs and RSU under the IDA mechanism. Then, taking psychological effects into account, we show the performance of the amended IDA mechanism.

In our simulations, we specify the payoff function $F_m(\boldsymbol{x}_m)$ of RSU m as

$$F_m(\boldsymbol{x}_m) = \log\left(1 + \sum_{n=1}^{N} x_{m,n}\right). \tag{47}$$

We can see that expression (47) satisfies the criteria discussed in Section III-A and the log term reflects the generic economic law of diminishing marginal returns. Similarly, we specify the cost function $C_n(\boldsymbol{y}_n)$ of EV n as

$$C_n(\boldsymbol{y}_n) = \exp\left(\sum_{m=1}^{M} y_{n,m}\right) - 1. \tag{48}$$

In addition, we set the step size $\delta = 0.05$ and the tolerance error $\epsilon_1 = \epsilon_2 = 0.001$ in Algorithm 1, and initialize the data request and offer matrices $\boldsymbol{X}^{(0)}$ and $\boldsymbol{Y}^{(0)}$, as well as the dual

TABLE I
INITIAL PARAMETER SETTING

Parameter		RSU 1	RSU 2	RSU 3	RSU 4	RSU 5
$\boldsymbol{X}$	EV 1	1.3629	1.7969	1.1338	1.0817	1.8823
	EV 2	1.2314	1.6143	1.4106	1.3455	1.5424
	EV 3	1.0519	1.6507	0.9887	1.3475	1.4467
	EV 4	1.4548	1.6136	1.1375	1.1534	1.2863
$\boldsymbol{Y}$	EV 1	0.0505	0.0398	0.0651	0.1468	0.0495
	EV 2	0.0442	0.0489	0.0525	0.0579	0.0471
	EV 3	0.0614	0.0381	0.0578	0.0622	0.0612
	EV 4	0.0261	0.0219	0.0347	0.0299	0.0348
$\boldsymbol{\mu}$	EV 1	0.5897	0.5108	0.6965	0.7725	0.5229
	EV 2	0.6392	0.5634	0.5839	0.6417	0.6358
	EV 3	0.7221	0.5521	0.7747	0.6409	0.6771
	EV 4	0.5593	0.5636	0.6946	0.7319	0.7596
		EV 1	EV 2	EV 3	EV 4	
$\boldsymbol{\lambda}$		0.1122	0.1966	0.1711	0.1399	

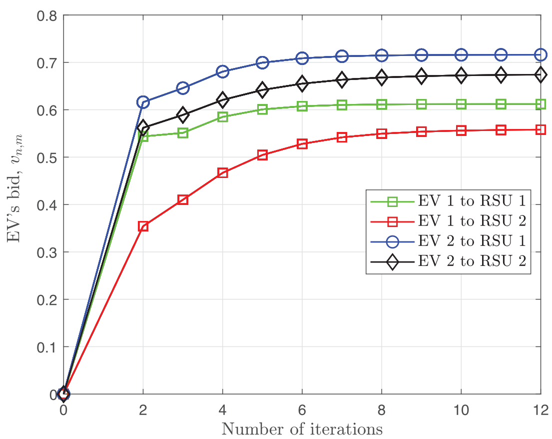

Fig. 5. Evolution of EVs' bids.

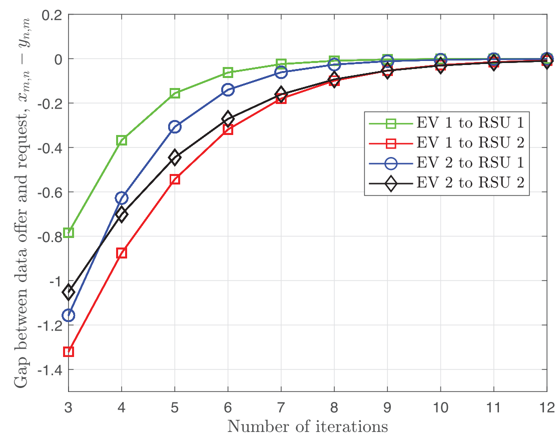

Fig. 6. Variation of the gap between data offer and data request.

variables $\boldsymbol{\lambda}^{(0)}$ and $\boldsymbol{\mu}^{(0)}$ as random values shown in Table I. Actually, the system parameters can be flexibly set in our simulations [44].

A. Performance of IDA Mechanism

We first plot Fig. 5 to show the evolution behavior of EVs' submitted bids with the number of iterations, where we consider the ecosystem consists of two RSUs and two EVs. We can observe from Fig. 5 that for every RSU–EV pair, the EV's bid shows a monotonically increasing trend and converges after about eight iterations, which demonstrates the proposed IDA mechanism has high convergence efficiency. It is worth mentioning that according to the update equations and iteration terminating conditions in Algorithm 1, we can know that when the EVs' bids converge, the RSUs' bids will also converge.

With the same settings as those in Fig. 5, we then summarize in Fig. 6, the variation of the gap between the data offer and data request (i.e., $y_{n,m}^{(t)} - x_{m,n}^{(t)}$), which is an important indicator for reflecting the market stability. Fig. 6 shows that as the iteration number increases the gap monotonically diminishes and finally tends to 0. It indicates that the proposed IDA mechanism can guarantee that the iterative interactions between two sides lead to an exact match point for the data request amount of RSUs and the data offer amount of EVs. The results of Figs. 5 and 6 reflect the operating law of the IDADET ecosystem in IoV, where RSUs and EVs bid separately, and the broker adjusts the data allocation and pricing until the amount of data offered by EVs and the amount of energy supplied by RSUs reach equilibrium.

Fig. 7 shows how the social welfare of the IDADET ecosystem varies with the iteration numbers of the IDA mechanism under different settings of step size δ, where we set $\delta = \{0.04, 0.05, 0.06\}$, $M = 5$, and $N = 5$. We can observe that in all cases the social welfare monotonically increases with the number of iterations and gradually converges to the maximum, which verifies the economic feasibility and convergence of the proposed IDA mechanism. We can also see that the step size does not change the achievable maximal social welfare but affects the speed of social welfare convergence. This is because the increase in step size will accelerate the evolution

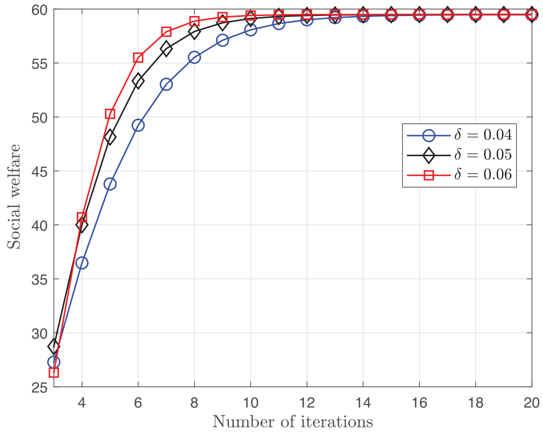

Fig. 7. Variation of social welfare.

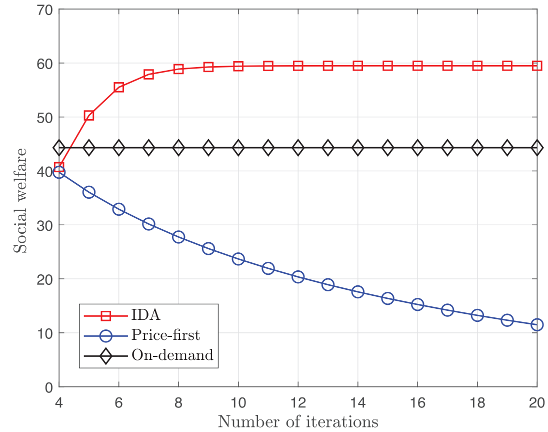

Fig. 9. Comparison with intuitive trading mechanisms.

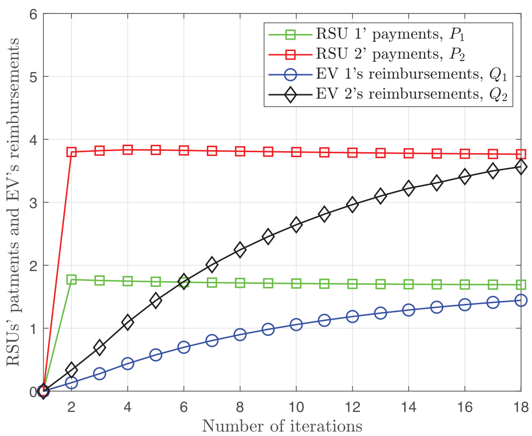

Fig. 8. Evolution of RSU's payments and EV's reimbursements.

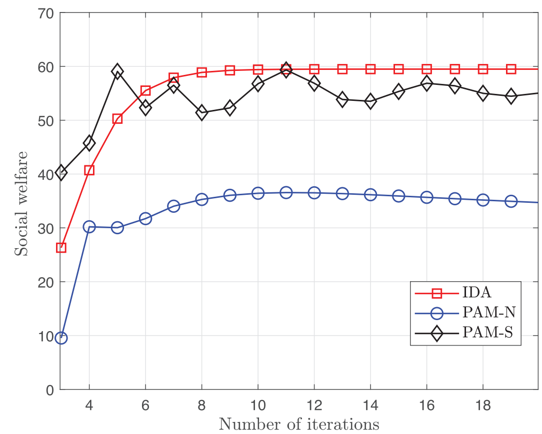

Fig. 10. Comparison with PAM-N and PAM-S mechanisms.

of dual variables in Algorithm 1 so that the social welfare reaches convergence quickly.

We plot Fig. 8 to show the evolution of RSU's payments and EV's reimbursements with the number of iterations. We can see that the iteration number increases, RSUs' payments increase instantly and then quickly become stable, while EVs' reimbursements increase gradually. An important observation from Fig. 8 is that the sum of RSU's payments is always higher than the sum of EVs' reimbursements, which is compatible with the assertion that the IDADET ecosystem satisfies the economic property of BB.

To demonstrate the efficiency of the IDA mechanism in terms of social welfare in the IoV-oriented data acquisition market, we first plot Fig. 9 to compare its performance with two mechanisms, i.e., Price-first and On-demand, which are intuitive strategies that decide the data allocation according to the order of pricing and data request amount, respectively [44]. Fig. 9 shows that as the number of iterations increases, different from the upward trend of the IDA mechanism, the social welfare of the On-demand mechanism remains largely unchanged and that of the Price-first mechanism declines significantly. This is because, for the On-demand mechanism, the variation of iteration numbers has no effect on data allocation, while for the Price-first mechanism, determining data allocation only by the order of pricing will incur malicious competition, thereby leading to a decline in social welfare. It indicates that although the operational rules of the intuitive mechanisms are straightforward and simple, they cannot guarantee good social welfare for the whole data acquisition market.

We further summarize in Fig. 10 the performance comparison in terms of the market social welfare of the IDA mechanism with two existing resource trading mechanisms, i.e., PAM-N and PAM-S [45]. The main difference between these trading mechanisms reflects in the rules of reimbursement. We can observe from Fig. 10 that as the number of iterations increases, the social welfare of all the mechanisms increases first, then, it converges soon for the IDA and PAM-N mechanisms but oscillates obviously for the PAM-S mechanism. In addition, Fig. 10 shows that the convergent social welfare of the IDA mechanism is remarkably higher than that of the PAM-N mechanism, and not lower than the peak of the oscillation curve of the PAM-S mechanism. It demonstrates the advantages of the developed IDADET ecosystem in terms of algorithmic convergence and achievable social welfare.

B. Performance of Amended IDA Mechanism

In the simulations for the amended IDA (A-IDA) mechanism, we set $M = 5$, $N = 4$, and initialize the Lagrangian

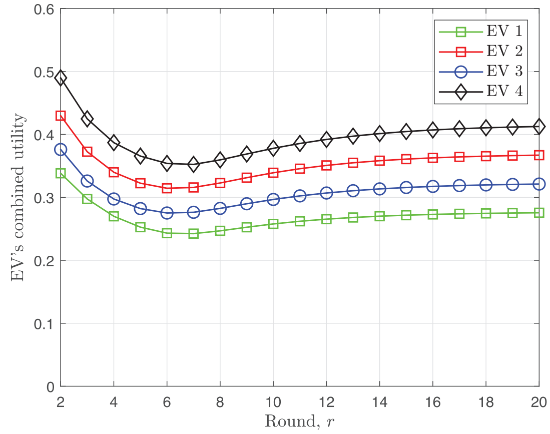

Fig. 11. Evolution of EV's combined utility under A-IDA mechanism.

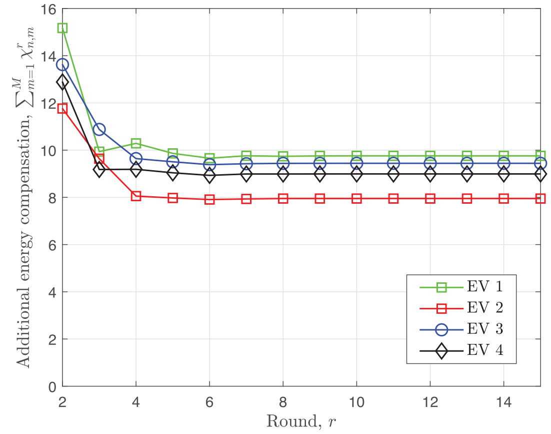

Fig. 13. Evolution of additional energy compensation under A-IDA mechanism.

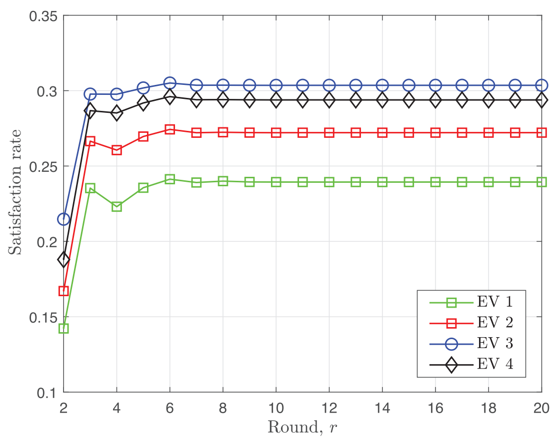

Fig. 12. Evolution of satisfaction rate under A-IDA mechanism.

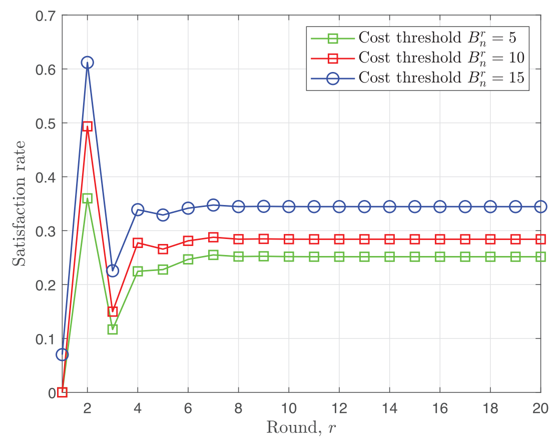

Fig. 14. Impact of cost threshold on satisfaction rate.

parameters and other system parameters by adopting uniformly distributed random values. We summarize in Fig. 11 the long-term evolution of the EV's combined utility in the IDADET ecosystem under the A-IDA mechanism. We can observe from Fig. 11 that the evolution trends of different EVs' combined utilities are similar, which first decrease, then slowly increase, and eventually tend toward stability. This is because when the combined utility of the EV decreases, the A-IDA mechanism can suppress the downward trend in time by giving the EV additional energy compensation, so that the combined utility can rebound and remain in a stable state. It indicates that the A-IDA mechanism can efficiently cope with the psychological loss of EVs and motivate them to participate in the IDADET ecosystem for a long time.

We then plot Fig. 12 to show the variation of the EV's satisfaction rate during the long-term participation in data acquisition tasks under the A-IDA mechanism. Note that in Fig. 12, each numerical point represents the sum of an EV's satisfaction rate with all RSUs, i.e., $\sum_{i=1}^{M} \rho_{n,m}^{r}$. It can be seen that as the number of rounds of data acquisition tasks increases, the EV's satisfaction rate swings (mainly in increasing) in the first few rounds and then tends to be stable. It indicates that by executing the A-IDA mechanism, EVs' psychological satisfaction will not decline with the increase in working time and, thus, they are willing to be engaged continuously in the IDADET ecosystem.

In Fig. 13, we show how the amount of additional energy compensation granted to EVs varies with the number of rounds of data acquisition tasks under the A-IDA mechanism. We can observe that as the number of rounds increases, the additional energy compensation of all EVs is somewhat reduced in the first few rounds and then tends toward stability. Such observation provides us with the significant insight that the additional energy compensation granted to EVs does not become uncontrollable as the number of rounds increases, instead, we only need to provide a limited amount of energy compensation to keep EVs participating in the IDADET ecosystem.

Finally, we plot Figs. 14 and 15 to show the impacts of the cost threshold and expected return on satisfaction rate. We can see that all the curves of satisfaction rate present fluctuations with the number of rounds and finally converge, this is because the satisfaction rate will tend to be stable with the stabilization of the additional energy compensation. Fig. 14 shows that a larger cost threshold can lead to a higher satisfaction rate. This is in line with the basic principle of behavioral economics: when the acceptable overhead is higher, then an entity will have a better experience during market participation. In the IDADET ecosystem, the larger the cost threshold of EVs, the

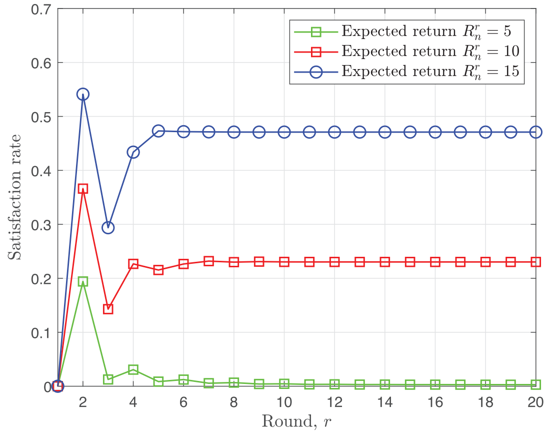

Fig. 15. Impact of expected return on satisfaction rate.

more additional energy compensation can be provided and, thus, the higher the satisfaction rate of EVs will be. We can observe from Fig. 15 that a larger expected return can result in a higher satisfaction rate. This is because when the expected return is larger, the psychological value generated by the unit payoff will also increase, and the satisfaction rate becomes higher. The phenomena presented in these figures demonstrate that the designed A-IDA mechanism fits with the basic laws of market behavioral economics.

VIII. Conclusion

In this article, we have proposed an IDADET ecosystem in the IoVs. To achieve SWM under incomplete market information, we have regulated the interactive behaviors among market participants by elaborately designing a set of operational rules covering data allocation, bidding, payment, and reimbursement. The economic feasibility of the IDADET ecosystem has been analyzed by proving its convergence and desirable properties of IR, BB, IC, and EE. Furthermore, we have also made amendments to the operational rules of the IDADET ecosystem from the behavioral economics perspective, to cope with the psychological effects of market participants and, thus, ensure the long-term well-functioning of the ecosystem. Extensive numerical simulations have been conducted to demonstrate the practical operability and performance behaviors of the IDADET ecosystem.

Note that in this study, the development of the IDADET ecosystem is on the basis of the underlying techniques' completeness. When formulating the SWM problem, we consider the properties of the data acquisition market while shielding the physical characteristics of the IoV. It is interesting to introduce the physical effects, such as energy transfer, wireless communications, and EVs' mobility into the problem formulation, but meanwhile, the problem solution and the design of the data transaction mechanism may become more sophisticated. Therefore, in our future work, we will further investigate the design of the IoV-oriented data acquisition market integrated with more practical network characteristics.

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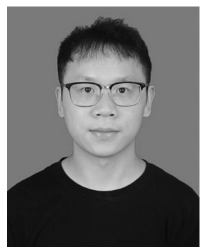
Yang Xu (Member, IEEE) received the B.E. degree from the School of Telecommunications Engineering and the Ph.D. degree from the Department of Communication and Information Systems, Xidian University, Xi'an, China, in 2006 and 2014, respectively.

She is currently an Associate Professor with the School of Computer Science and Technology, Xidian University. She has published over 50 academic papers at premium international journals and conferences, such as the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, the IEEE TRANSACTIONS ON MOBILE COMPUTING, the IEEE INTERNET OF THINGS JOURNAL, the IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY, and the IEEE INFOCOM. Her research interests include wireless communications security, mobile crowd sensing, network economics, block-chain technology, and routing protocol design.



Honggang He (Graduate Student Member, IEEE) is currently pursuing the master's degree with the School of Economics and Management, Xidian University, Xi'an, China.

His research interests include game theory and network economics.

Jia Liu (Member, IEEE) received the B.E. degree from the School of Telecommunications Engineering, Xidian University, Xi'an, China, in 2010, and the Ph.D. degree from the School of Systems Information Science, Future University Hakodate, Hakodate, Japan, in 2016.

His research interests include wireless systems security, space–air–ground integrated networks, Internet of Things, and 5G. He has published over 50 academic papers at premium international journals and conferences, such as the IEEE TRANSACTIONS ON WIRELESS COMMUNICATIONS, the IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY, and the IEEE INFOCOM.

Dr. Liu received the 2016 and 2020 IEEE Sapporo Section Encouragement Award.

Yulong Shen (Member, IEEE) received the B.S. and M.S. degrees in computer science and the Ph.D. degree in cryptography from Xidian University, Xi'an, China, in 2002, 2005, and 2008, respectively.

He is currently a Professor with the School of Computer Science and Technology, Xidian University, where he is also an Associate Director of the Shaanxi Key Laboratory of Network and System Security and a member of the State Key Laboratory of Integrated Services Networks. His research interests include wireless network security and cloud computing security.

Prof. Shen has also served on the technical program committees of several international conferences, including ICEBE, INCoS, CIS, and SOWN.

Tarik Taleb (Senior Member, IEEE) received the B.E. degree (with Distinction) in information engineering and the M.Sc. and Ph.D. degrees in information sciences from Tohoku University, Sendai, Japan, in 2001, 2003, and 2005, respectively.

He is currently a Professor with the Center of Wireless Communications, University of Oulu, Oulu, Finland, where he is the Founder and the Director of the MOSA!C Lab. From October 2014 to December 2021, he was a Professor with the School of Electrical Engineering, Aalto University, Espoo, Finland. Prior to that, he was working as a Senior Researcher and a 3GPP Standards Expert with NEC Europe Ltd., Heidelberg, Germany. Before joining NEC and until March 2009, he worked as an Assistant Professor with the Graduate School of Information Sciences, Tohoku University, in a lab fully funded by KDDI, the second largest mobile operator in Japan. From October 2005 to March 2006, he worked as a Research Fellow with the Intelligent Cosmos Research Institute, Sendai. He has also been directly engaged in the development and standardization of the Evolved Packet System as a member of 3GPP's System Architecture Working Group 2. His research interests lie in the field of telco cloud, network softwarization and network slicing, AI-based software-defined security, immersive communications, mobile multimedia streaming, and next generation mobile networking.

Prof. Taleb is the recipient of the 2021 IEEE ComSoc Wireless Communications Technical Committee Recognition Award in December 2021, the 2017 IEEE ComSoc Communications Software Technical Achievement Award in December 2017 for his outstanding contributions to network softwarization. He is also the (co-)recipient of the 2017 IEEE Communications Society Fred W. Ellersick Prize in May 2017, the 2009 IEEE ComSoc Asia–Pacific Best Young Researcher Award in June 2009, the 2008 TELECOM System Technology Award from the Telecommunications Advancement Foundation in March 2008, the 2007 Funai Foundation Science Promotion Award in April 2007, the 2006 IEEE Computer Society Japan Chapter Young Author Award in December 2006, the Niwa Yasujirou Memorial Award in February 2005, and the Young Researcher's Encouragement Award from the Japan Chapter of the IEEE Vehicular Technology Society in October 2003. Some of his research works have also been awarded the best paper awards at prestigious IEEE flagged conferences. He served on the IEEE Communications Society Standardization Program Development Board. He served as the General Chair of the 2019 edition of the IEEE Wireless Communications and Networking Conference held in Marrakech, Morocco. He was the Guest Editor-in-Chief of the IEEE JOURNAL ON SELECTED AREAS IN COMMUNICATIONS Series on Network Softwarization and Enablers. He was on the editorial board of different IEEE journals and magazines. Until December 2016, he served as the Chair of the Wireless Communications Technical Committee, the largest in IEEE ComSoC.

Norio Shiratori (Life Fellow, IEEE) is currently a Professor with Chuo University, Tokyo, Tokyo, and also an Emeritus Professor with Tohoku University, Sendai, Japan. He has published over 15 books and over 600 refereed papers in computer science and related fields.

Dr. Norio was a recipient of the Minister of MEXT Award from the Japanese Government in 2016, the Science and Technology Award from the Ministry of Education, Culture, Sports, Science, and Technology (MEXT) in 2009, the Institute of Electronics, Information and Communication Engineers (IEICE) Achievement Award in 2001, the IEICE Contribution Award in 2011, the Information Processing Society of Japan (IPSJ) Contribution Award in 2008, the IEICE Honorary Member in 2012, the IPSJ Honorary Member in 2013, the IPSJ Memorial Prize Winning Paper Award in 1985, the IPSJ Best Paper Award in 1997, the IEICE Best Paper Award in 2001, the IEEE 5th SCE01 Best Paper Award in 2001, the IEEE ICPADS 2000 Best Paper Award in 2000, and the IEEE 12th ICOIN Best Paper Award. He was a former President of IPSJ from 2009 to 2011. He is a Fellow of the Japan Foundation of Engineering Societies, IPSJ, and IEICE.