TIDES: A Trust-Aware IoT Data Economic System With Blockchain-Enabled Multi-Access Edge Computing

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This work was supported by the Ministry of Science and Technology (MOST), Taiwan, under Grant 106-2221-E-006-244-MY3, Grant 107-2221-E-006-164-MY2, and Grant 108-2321-B-006-008.

ABSTRACT To make good use of valuable Internet of Things (IoT) data assets, this paper proposes a trust-aware IoT data economic system (TIDES) with complete IoT data pricing, trading and protection functions. To ensure reliable and automatic data trading, the entire trading process is automatically performed by smart contracts on a hierarchical blockchain. Moreover, we develop several sophisticated methods to ensure the efficiency and service quality of TIDES. First, a complete evaluation model that takes the data trading profile and reputation into consideration is proposed for both suppliers and demanders to assess the trustworthiness of their trading partners. Second, a client-centric data value evaluation model and a game-theory-based pricing model are used to promote win-win transactions in which the demanders obtain higher quality data at an acceptable price and the suppliers receive higher profits. Third, a dispute arbitration model is invoked to detect suspicious trading and refund these payments automatically. TIDES further utilizes a multi-access edge computing (MEC) architecture to alleviate the huge burdens of IoT devices from blockchain operations, reduce the trading latency, and help mobile devices to trade IoT data. The simulation results have shown the advantages of TIDES in terms of trading time, storage overhead, data trading profit, quality data trading, pricing efficiency, and reliability on data asset management and trading.

INDEX TERMS Blockchain, data economy, data trading, edge computing, Internet of Things (IoT).

I. INTRODUCTION

With the emergence of Internet of Things (IoT), various IoT devices are widely deployed to realize a wide variety of smart cyber-physical systems (CPSs), such as intelligent transportation systems and smart grids, where data are the most valuable assets. However, a large IoT deployment for only one silo application is not easy to sustain. Additionally, complex data-intensive applications usually need data from multiple sources; therefore, IoT service providers tend to purchase data from multiple sources. Thus, IoT data trading is becoming active, and the establishment of trustworthy and reliable IoT data economic systems has become a necessity.

Such systems must be able to efficiently manage the lifecycle of IoT data, which typically consists of stages: data collection, data analytics, data pricing, data trading, and data protection [1]. During data collection and data analytics, massive amounts of heterogeneous data are collected and applied to generate useful knowledge, and the results are called data services. However, these two stages often suffer from the problems of inefficient data access and changeable data quality. To valuate the provisioning of data services, deciding how to charge for the services occurs in the data pricing stage. However, in a highly dynamic market, deriving an immutable pricing strategy for diverse IoT applications is practically infeasible. In the data trading stage, the demanders decide their target data and the suppliers ship their commodity. However, an untrusted supplier might provide counterparts, and on the other hand, a deadbeat could bilk, which leads to unreliable transactions. In addition, because IoT data are usually sensitive and valuable, cybersecurity for data storage and data delivery is ensured at the data protection stage.
Finally, to sustain applicable IoT services, all operations in these five stages are required to perform automatically [2] and efficiently and to easily support mobile devices.

A solid IoT data economic system, including the proposed trust-aware IoT data economic system (TIDES), should be designed to fulfill some critical requirements. The most important requirement is reliability. For this requirement, the system should provide stable trading services and further prevent trading and its records from manipulating and dominating. The confidentiality of data storage and data delivery also needs to be protected. Finally, when one side in a transaction is malicious, the system should be able to rapidly address this situation. However, traditional trading systems usually provide services from centralized servers that are vulnerable to single points of failure, which might lead to system unreliability. Intelligence is required to guarantee service quality so that the system can smartly help both demanders and suppliers to make decisions based on their expectations. According to the hypothesis of rational people [3], suppliers tend to maximize their profits, and demanders want to obtain the most satisfactory commodity at an acceptable price. Generally, a higher price increases profits but reduces the purchase intention which is also related to commodity quality. The existence of competitors also influences the probability of transactions. Thus, for suppliers, providing a pricing strategy that considers the variable market situation to maximize profits is a necessity. For demanders, the first thing they need to do before purchasing a data commodity is to assess its value, which is related to data quality. Automation is an inevitable requirement for trading, and the massive IoT data necessitates an algorithmic trading mechanism [4] without manual intervention. Efficiency is also highly demanded; thus, latency and resource utilization need to be taken into consideration. The time for a data transaction includes both the trading time and the access time. The volume of IoT data always leads to heavy burdens on data access, while a complicated data trading mechanism takes a very long trading time. Moreover, as most IoT data are queried locally, not all data need to be delivered globally. To this end, edge computing is a promising solution that benefits not only system performance but also network resource utilization. Finally, the requirement for mobility management cannot be ignored. As both data suppliers and data demanders can be either mobile users or IoT devices, they might need to create transactions when moving.

There have been several blockchain-based solutions for distributed data trading [5]–[8]. A publish/subscribe framework [5] was proposed by Hashemi et al. Roman and Stefano proposed a trusted data marketplace architecture by evaluating user credit [6], and both the demander and the supplier have to sign a smart contract to manage their operations by manual intervention. Filecoin [7], similar to Bitcoin [8], is a data storage service that applies the concept of proof-of-retrievability. It encourages nodes to contribute their storage as much as possible. Although these distributed data trading systems alleviate the problems of centralized systems, they neither provide IoT data pricing strategies nor handle trading disputes, and hence fail to fulfill the intelligence and reliability requirements as indicated above.

In our previous work [9], the reliable IoT data economic system (RIDES) was proposed to provide IoT data as a foundation trading service. This paper further presents TIDES, which carries out the holistic functions of data pricing, trading, and protection. This system also provides secure and tamper-proof data trading channels with a hierarchical blockchain that fulfills the reliability requirement. Owing to the decentralization property of blockchain technology, users can trade fairly without being dominated. The secure design of TIDES for IoT data lifecycle management also ensures reliable data storage and delivery. To ensure trading reliability, an integrated evaluation model that takes the data trading profile and reputation into account is proposed for both suppliers and demanders to assess the trustworthiness of their trading partners and further reduce the trading failure rate. Even if the demander has unfortunately created a transaction with a malicious supplier, its payment can be refunded automatically through a dispute arbitration procedure. To fulfill the intelligence requirement, on the supplier side, we propose an intelligent, game-theoretical pricing model in accordance with the pricing strategies of competitors to determine an appropriate price. This pricing model gives the suppliers notably higher profits than other models. On the demander side, a client-centric data value evaluation model is used to evaluate the data value and determine which data commodity is worth purchasing. With this model, the demanders can obtain satisfactory data commodities at acceptable prices. To address the automation requirement, all trading procedures in TIDES are algorithmic and performed automatically by exploiting the smart contract technique. Furthermore, TIDES applies the multi-access edge computing (MEC) paradigm [12] with a hierarchical blockchain. With this efficient data trading architecture, the burden on IoT devices can be alleviated and the mobility issue can be solved. Therefore, TIDES also fulfills the requirements of efficiency and mobility. Then, thorough simulations are conducted. The simulation results demonstrate that the system performance and storage overheads of TIDES are better than those of existing systems. The increased profit, higher quality data trading and better pricing efficiency brought by the proposed intelligent pricing model and the improved trading reliability due to the trustworthiness evaluation also show the advantage of TIDES. To the best of our knowledge, TIDES is the first and most complete system proposed to efficiently provide IoT data commodities with a reliable, intelligent, and automatic trading environment.

The paper is organized as follows. Section II provides background information related to this work. Section III describes the details of the system architecture, and Section IV presents the proposed methods for reliability and trust-awareness design. The system flows of TIDES are described in Section V. Then, the simulation results for TIDES are shown in Section VI. Finally, the concluding remarks for this paper are given in Section VII, and the abbreviations used in this paper are summarized in the appendix.
II. BACKGROUND
A. BLOCKCHAIN TECHNOLOGY AND SMART CONTRACT
Blockchain is an emerging technology whose immutability allows it to reliably store data. Bitcoin [8] is the first successful blockchain-based cryptocurrency, and Ethereum [10] further improves blockchain as a programmable distributed trusted infrastructure. The core technique making Ethereum programmable is the smart contract, which is a self-executing data structure described in high-level languages, such as Python, compiled into bytecode, and then executed by all nodes equipped with the Ethereum Virtual Machine. A smart contract can apply conditional expressions to describe a deterministic environment. When a condition described in a smart contract is satisfied, an activation transaction will be deployed to the blockchain network to activate the smart contract. Then, the corresponding trading specified in the smart contract will be performed. In an Ethereum smart contract, the Contract ID and application binary interface (ABI) [11] with bytecode are the most important information. The former indicates where the smart contract is, and the latter describes the content of smart contracts for human reading. In addition, some trading information, such as data URLs, can also be stored in a smart contract to detail the trading.

B. MULTI-ACCESS EDGE COMPUTING (MEC)
In the past, cloud computing was widely applied to all types of services. However, the volume of IoT data has congested cloud servers leading to the denial of service. The high network latency between cloud servers and IoT devices also makes cloud computing technology inapplicable in high-speed IoT applications. Therefore, the MEC architecture has been proposed to provide additional resources, such as computing power and storage space, at the edge side, which can fulfill the low-latency requirement of IoT services while significantly alleviating the cloud server loads [13]. As MEC services are usually provided by network service providers, the roaming problem of mobile devices can also be addressed.

C. DATA PRICING MODEL
The data pricing models can be categorized into two types [1]. The economic-based pricing model evaluates the price of data according to economic principles, such as costs and margins. The game-theory-based pricing model considers competitor behaviors before pricing.

1) ECONOMIC-BASED PRICING MODELS
- Cost model [14]: This model considers only the commodity costs and profit margins. The simplicity of this model is a remarkable advantage. However, the lack of external information leading to market misjudgment also makes it ineffective in data trading [15].
- Consumer perceived model [16]: The suppliers using this model take the demander’s feedback into account. In general, this model is more suitable for data pricing than the cost model. However, ignoring supply conditions makes it difficult to derive the most appropriate price.
- Supply and demand model [17], [18]: In this kind of model, the relationship between suppliers and demanders is the most important factor for pricing. In [17], a linear supply function and a linear demand function are formulated to derive the price. In [18], a pricing system, called MGA, is proposed by formulating the willingness of suppliers and demanders as two natural logarithmic functions. Although the intersection of supplier and demander functions implies the price that has the best probability to reach a deal, the neglect of market situations, such as the competition between suppliers, leads to inappropriate pricing.

2) GAME-THEORY-BASED PRICING MODELS
- Non-cooperative game model [19], [20]: In [19], suppliers do not need to negotiate with each other. Instead, suppliers derive their prices by referring to the pricing strategies announced by other suppliers. This model is applicable in IoT environments but might result in a price war. Exploiting a centralized broker, the authors of [20] proposed a pricing method that takes all demanders and suppliers into account to derive appropriate prices without price cutting. However, since numerous transactions for IoT data will be created dynamically, a centralized pricing system, which usually becomes a performance bottleneck, is unpractical for IoT data trading.
- Stackelberg game model [21]–[23]: In this kind of model, each supplier announces its price after the major supplier does. In the IoT data trading environment, however, the determination of the major supplier is difficult and inefficient, which makes this model impractical.
- Bargaining game model [24]: In this model, suppliers and demanders negotiate to reach an agreement. Nevertheless, the negotiation process is usually time-consuming and resource-wasting. Thus, this model is not suitable in the IoT data trading scenario.

III. TRUST-AWARE IOT DATA ECONOMIC SYSTEM
Fig. 1 and Fig. 2 show the functional model and system architecture of TIDES based on the MEC infrastructure where the data suppliers and data demanders could be human-operated devices or autonomous IoT devices within each radio access network (RAN) area. An IoT device or user equipment may play the roles of both supplier and demander. For resource-constrained data suppliers and demanders, IoT gateways can be the intermediaries between them and TIDES. As shown in Fig. 2, TIDES contains the functional entities of data repositories (DRs), an information broadcasting station (IBS), data trading agencies (DTAs), a data trading blockchain (DTB), and a transaction dispute arbiter (TDA) to constitute a complete ecosystem of the IoT data economy. DRs implement a decentralized data storage scheme that can adapt to different requirements for data privacy, access speed,
FIGURE 1. The functional model of TIDES.

FIGURE 2. The MEC-based system architecture of TIDES.

and storage capacity. DTAs allow data trading stakeholders to draw smart contracts and accomplish each data transaction. IBS is commissioned to advertise the smart contracts announced by data suppliers, the service specification of each DR entity, and the service specification of each DTA. TDA is authorized to arbitrate the disputes of IoT data transactions. These four types of functional entities are for public cloud services with avatars on ME hosts. A cloud-edge coordination mechanism is designed for each cloud site and its edge avatars to fully exploit the advantages of MEC. DTB is implemented on the Ethereum platform to provide a secure and tamper-proof financial flow for data trading. It also adopts a hierarchical structure that consists of a main chain over the Internet and multiple local chains on ME hosts. In TIDES, IBS, TDA and DTB are public services, while DR and DTA are contract-based services.

Based on the algorithmic trading mechanism [4], TIDES realizes a trust-aware algorithmic data trading scenario. On the supply side, when a supplier acquires a new IoT data asset, it encrypts the asset, and then deposits the encrypted asset in a commissioned DR. In addition, the supplier prices the data asset and draws a smart contract to sell this asset by consulting a DTA. The contract is then deployed to DTB through DTA and announced on IBS. On the demand side, every demander smartly chooses what it wants by referring to the advertisements announced on IBS. Then, it starts to purchase the chosen data commodity according to the corresponding smart contact in DTB and accomplishes the payment to the assigned account. After the payment has been transferred to the data supplier, the purchased data commodity and its corresponding key can be delivered to the demander securely. Next, the demander verifies whether the received data are satisfactory. If any argument occurs, it can request the TDA to arbitrate, and obtain the refund once this request is approved. The details of the operational flows will be introduced in Section IV.

From the viewpoint of commercial business, TIDES can have multiple DTAs with their own service know-how. As depicted in Fig. 1, each specific DTA deploys its edge agents on ME hosts in different RANs to serve nearby suppliers and demanders. These edge agents allow IoT devices to make local data trades, and each of them deploys smart
contracts into the local chain of DTB on the same ME host under the commissions from data suppliers. To provide its data asset for global usage, the supplier designates its smart contract to be deployed to the main chain of DTB. Then, the commissioned DTA edge agent transfers this smart contract deployment task to its cloud server. Similarly, one demander delegates a DTA edge agent to purchase a data commodity from the local chain of DTB in the same RAN. If the data commodity is supplied by a cloud DR or an edge DR in another RAN, then the delegated edge agent will transfer the task to its DTA cloud server to activate the target smart contract from the main chain of DTB. Purchasing a data commodity from another RAN requires more collaboration between the DTA cloud server and the corresponding edge agents.

As shown in Fig. 1 and Fig. 2, the local interactions of functional entities on the same ME host can achieve most of the TIDES functions for the data suppliers and demanders in the same RAN, which can make data trading more efficient and even more reliable. The IBS edge agents and TDA edge agents have similar edge-cloud collaboration scenarios to that of DTA. Each IBS edge agent advertises the smart contracts and the DR edge centers for local clients in the same RAN, while the IBS cloud server collects advertisements for global clients. Each TDA edge agent serves the dispute arbitration requests from demanders in the same RAN. When receiving an arbitration request to the data supplier in another RAN, the TDA edge agent will transfer this task to the TDA cloud server to coordinate the arbitration procedure between the corresponding edge agents.

As other functional entities, TIDES also implements a data repository with a hierarchical structure, which consists of DR cloud centers and their edge agents. Different DRs have different service strategies. For privacy and security considerations, the traded data commodity may be stored in the private storage of a data supplier or an IoT gateway. In this case, the traded data set will be directly delivered from the supplier to the demander.

The structure of the smart contract for IoT data trading in TIDES, which is composed of contract ID, contract ABI with bytecode, and trading information, is shown in Fig. 3(a). The former two parts follow the rules defined in Ethereum. The last part consists of four fields. The DR field details the ID of DR and the location where the data asset is stored. The DTA field names the ID of the commissioned DTA. The trading field describes the traded data. The optional field enumerates additional information about the trade, such as the supplier’s public key. When the data supplier receives a payment for a smart contract that it announced, it provides the DR URL and data wrapped key for this transaction in the smart contract. Then, the demander can obtain the traded data from the DR and the data wrapped key from blockchain. In addition, Fig. 3(b) shows the information described in a smart contract advertisement.

### IV. SECURITY, PRICING, AND TRUST-AWARENESS MODELS IN TIDES

#### A. SECURITY DESIGN FOR IoT DATA LIFECYCLE MANAGEMENT

TIDES employs multiple data protection mechanisms at the infrastructure layer and the data layer.

1) **SECURITY DESIGN AT THE INFRASTRUCTURE LAYER**

In TIDES, all functional entities interact through secure channels constructed by means of the security architecture of 5G MEC and the network slicing scheme to ensure communication security. Blockchain technology also guarantees the integrity and temporal consistency of all transactions to sustain reliable data trading.

2) **SECURITY DESIGN AT THE DATA LAYER**

The security design at the data layer intends to prevent IoT data assets from being disclosed to unauthorized users or devices, and this design is mainly implemented in IoT devices, user equipment, and IoT gateways. The functional components of stand-alone data suppliers and demanders are depicted in Fig. 1, while the functional structure of the IoT gateway that helps resource-constrained data suppliers and demanders to accomplish their data trading operations is illustrated in Fig. 4.
TIDES employs a series of encryption schemes to prevent data assets from unauthorized access while ensuring the originator identity. Whenever a supplier acquires a new data set, this device or its IoT gateway invokes the data encryptor to encrypt the data set with a random key, Key_r, as in (1).

\[ Data_e = E_s(\text{Data}_p, \text{Key}_r) \]  

where \( E_s(x, y) \) indicates a symmetric encryption operation to encrypt the data \( x \) with the key \( y \), while \( Data_p \) represents the plain data set and \( Data_e \) is the encrypted one. The \( Data_e \) will be stored in a data repository, and the \( Key_r \) is held by the supplier. Then, whenever the data supplier receives the payment notification for an approved data transaction, it invokes the wrapped key generator to generate the data wrapped key, Key_w, of \( Key_r \) by (2).

\[ Key_w = E_d(\left(E_s(\text{Key}_r, Key_{pub}^d), Key_{pri}^d\right)) \]  

where \( E_d(x, y) \) represents the asymmetric encryption operation to encrypt the data \( x \) with key \( y \), \( Key_{pub}^d \) is the public key of the demander retrieved from the payment notification, and \( Key_{pri}^d \) is the private key of the supplier. After receiving \( Key_w \), the demander invokes its data decryptor to derive \( Key_r \) by (3).

\[ Key_r = D_u(\left(D_s(\text{Key}_w, Key_{pub}^u), Key_{pri}^u\right)) \]  

where \( D_u(x, y) \) indicates the asymmetric decryption operation to decrypt the encrypted data \( x \) with key \( y \), \( Key_{pri}^u \) is the private key of the demander, and \( Key_{pub}^u \) is the public key of the supplier retrieved from the smart contact. With \( Key_r \), \( Data_e \) can be decrypted via symmetric decryption, \( D_s(x, y) \), where \( x \) is the encrypted data and \( y \) is the key for obtaining the original data set \( Data_p \) by (4).

\[ Data_p = D_s(Data_e, Key_r) \]  

**B. TRUSTWORTHINESS EVALUATION MODELS**

Trust is a key factor of satisfactory IoT data trading. Thus, TIDES proposes trustworthiness evaluation mechanisms for suppliers and demanders to assess the trustworthiness of their trading partners.

For user \( d \), the trustworthiness \( Trust_s^d \) of a potential trading partner \( s \) can be derived in (5)

\[ Trust_s^d = \beta \cdot OT_s + (1 - \beta) \cdot ST_s^d, \quad 0 \leq \beta \leq 1 \]  

where \( OT_s \) indicates the objective trustworthiness of \( s \), \( ST_s^d \) is the subjective trustworthiness of \( s \) for \( d \), and \( \beta \) is a weighting factor. First, user \( d \) will consult its DTA, whose trust evaluator provides the trustworthiness evaluation service for data trading stakeholders. All involved information for the trustworthiness evaluation should be tamper-proof and accessible. Therefore, the trust evaluator refers to only the trading records and account balance on DTB and the arbitration records on TDA when deriving \( OT_s \). Because it is more sophisticated for a trading partner with more transactions, the trust evaluator considers the number of transactions that has been completed by \( s \), \( Trans_s \), as a parameter. In addition, a trading partner with more arbitration records means it is not reliable. Hence, the trust evaluator retrieves the arbitration records \( Ret_s \) of \( s \) from TDA as a parameter. Moreover, a wealthy supplier usually has less motivation to maliciously provide incorrect data and has a greater capability to pay compensation, whereas a wealthy demander usually has less possibility of fraud in data transactions. Hence, the trust evaluator also takes the account balance \( AB_s \) of its trading partner into account. As a result, \( OT_s \) can be defined as a linear combination of the three parameters in (6).

\[ OT_s = \varepsilon_1 \left(\frac{Trans_s}{Trans_{all}}\right) + \varepsilon_2 \left(\frac{Ret_s}{Ret_{all}}\right) + \varepsilon_3 \left(\frac{AB_s}{AB_{all}}\right) \]  

where \( Trans_{all} \) and \( AB_{all} \) indicates the total number of transactions and amount of crypto-currency in TIDES, respectively, and \( \varepsilon_1, \varepsilon_2, \varepsilon_3 \) are the weighting factors such that \( \varepsilon_1 + \varepsilon_2 + \varepsilon_3 = 1 \).

To assess \( ST_s^d \), the trust evaluator considers the social relationship between \( s \) and \( d \) as a key factor because generally, a trading partner with more common friends is more trustworthy [25], [26]. In other words, \( s \) will be more worthy of \( d \)’s trust if it has more common trading partners with \( d \). Thus, \( ST_s^d \) is defined as the proportion of common trading partners between \( s \) and \( d \) with respect to the number of all trading partners of \( d \) in the trading records of TIDES.

\[ ST_s^d = \frac{|TP_d \cap TP_s|}{|TP_d|} \]  

Here, \(|TP_d|\) and \(|TP_s|\) respectively denote the number of trading partners of \( d \) and \( s \) in their data trading records, and \(|TP_d \cap TP_s|\) is the number of common trading partners between \( d \) and \( s \). The information of trading partnership can be discovered in DTB.

**C. DATA VALUE EVALUATION AND PRICING MODELS**

Accurately evaluating data values and appropriately deciding data prices are two important issues for demanders and suppliers to achieve successful data trading. Generally, suppliers would like to obtain the most profit, which might decrease the purchase intention [14], and demanders want to buy the data commodity with better quality at an acceptable price. Thus, for demanders, TIDES proposes the client-centric data value evaluation model to assess data values and further determine what to buy based on data values and data prices. To ensure a data trading reliability, the trustworthiness of the data supplier will also be taken into account. For suppliers, TIDES proposes an intelligent pricing model based on an enhanced game-theory method.

1) **CLIENT-CENTRIC DATA VALUE EVALUATION MODEL FOR DEMANDERS**

The market value of a data asset is usually related to its quality satisfaction (QS) degree with respect to the requirements of the demander. The QS of a data asset, DA, with respect to the...
quality requirements of demander \(d\), \(Q_{s_d}^{DA}\), is given by (8):

\[
Q_{s_d}^{DA} = \min_{k \in QA} \left\{ \frac{q_{s_d}^{DA}(k)}{r_{q_d}^{DA}(k)} \right\},
\]

where \(QA\) denotes a set of quality attributes such as precision, granularity and integrity for a data asset, \(q_{s_d}^{DA}(k)\) is the quality value of attribute \(k\) of \(DA\), announced by its supplier \(s\) in a smart contract, and \(r_{q_d}^{DA}(k)\) is the required quality value of \(d\) on \(k\) for \(DA\). According to the evaluation result of \(Q_{s_d}^{DA}\), the value of \(DA\), \(v_{s_d}^{DA}\), for demander \(d\) can be derived as given by (9).

\[
v_{s_d}^{DA} = \begin{cases} p_{s}^{DA} \cdot Trust_{s}^{d}, & \text{if } Q_{s_d}^{DA} \geq 1 \\ 0, & \text{otherwise} \end{cases}
\]

where \(p_{s}^{DA}\) is the average selling price of data commodities of the same type and quality as \(DA\) in TIDES. Since all trading information is recorded, the selling prices of all data sets can be inquired in data trading KB, and \(p_{s}^{DA}\) can be regarded as the objective value of \(DA\). For a demander, the value of a data set is also influenced by the trustworthiness of its data supplier. Thus, as in (9), \(Trust_{s}^{d}\), which is the trustworthiness of \(s\) for \(d\), is also taken into account. Note that \(Q_{s_d}^{DA}\) must be greater than one because otherwise, \(DA\) would be disqualified for the demander. As concluded in [18] and [27], demanders intend to purchase the data commodity with higher C-P ratio. Thus, TIDES estimates the C-P ratio if \(d\) purchases \(DA\) as follows,

\[
CP_{d}^{DA} = \begin{cases} \frac{P_{d}^{DA}}{p_{s}^{DA}}, & \text{if } p_{s}^{DA} < PL_{d}^{DA} \\ 0, & \text{otherwise} \end{cases}
\]

where \(P_{d}^{DA}\) is the price of \(DA\) set by \(s\), and \(PL_{d}^{DA}\) is the acceptable price of \(DA\) set by \(d\). After \(PL_{d}^{DA}\) is determined, it will be delivered by \(d\) to its DTA agent for further usage. For simplification, it is supposed that \(d\) will assign the same acceptable price to the data commodities with the same type and quality.

In TIDES, a demander first defines the acceptable price for the data asset that it wants to purchase before performing the client-centric data value evaluation model. Then, it consults the data value evaluator of its DTA agent to compute the C-P ratio of each candidate data commodity. The evaluator will refer to the value of \(P_{s}^{DA}\) from the data trading KB and the value of \(Trust_{s}^{d}\) from the client DB. These two values are maintained by the KB maintainer which continuously analyzes the trading records and market feedback information in TIDES. Then, the demander can decide whether it purchases \(DA\) or not by referring to \(CP_{d}^{DA}\).

2) GAME-THEORY-BASED PRICING MODEL FOR SUPPLIER

To construct a smart contract for selling an IoT data asset, \(DA_s\), the supplier \(s\) consults with its DTA. Its smart contract constructor will ask for a suggestion from the DTA’s data price analyzer about the price of \(DA_s\), and then the analyzer will refer to the data trading KB to respond this inquiry.

In addition, the DTA’s KB maintainer employs the following game-theory-based pricing model to update the data trading KB by referring to the historical information of data trading over TIDES.

For a supplier, both the demand and supply statuses and the bids from competitors significantly influence the probability of successful trading. Thus, an appropriate pricing strategy, such as the game-theory-based pricing model, should take the market situation into account. However, as mentioned in Section II, both the Stackelberg game model and the bargaining game model are impractical in IoT data trading. Traditional non-cooperative game models are more efficient but usually lead to a price war. Hence, by combining the economic-based pricing concept and the non-cooperative game model, TIDES proposes an enhanced game-theory-based pricing model that not only considers the market situation but also avoids low price competition. The proposed pricing model is introduced in the following section.

Similar to the cost model, the price of any data commodity offered by the supplier, \(s\), can be formulated into a general form as described in (11):

\[
p_{s}^{DA} = cost_s^{DA} \cdot \left(1 + m_{s}^{DA}\right), \quad m_{s}^{DA} > 0
\]

where \(cost_s^{DA}\) denotes the cost spent to acquire and maintain a data set \(DA\), and \(m_{s}^{DA}\) is the margin that \(s\) would like to obtain from selling \(DA\). The main goal of TIDES is to find an \(m_{s}^{DA}\) that makes the decided selling price of \(DA\) generate the most profit for \(s\). However, \(P_{s}^{DA}\) considers only the expectation of the data supplier. Referring to the consumer perceived model, our pricing model also takes the willingness of demanders into account. Since the intention that a demander purchases a commodity is related to its C-P ratio, the supplier should estimate the C-P ratio for its data commodity to be sold in the market by (12):

\[
CP_{est} = \frac{P_{s}^{DA}}{p_{s}^{DA}}
\]

where \(P_{s}^{DA}\) can be obtained from the data trading KB. Then, based on [18], our pricing model proposes an exponential-based S function as in (13) for the supplier \(s\) to estimate the purchase intention of demanders to buy \(DA\):

\[
P_{I_s}^{DA} = \left(1 + e^{-\left(\frac{CP_{est} - \beta}{\gamma}\right)}\right)^{-1}
\]

where \(\gamma\) and \(\beta\) are two pre-defined system parameters.

Then, the probability that a demander decides to purchase \(DA\) can be derived as in (14) by referring to the purchase intention of all data commodities, which have the same type as \(DA\), from other suppliers,

\[
P_{I_s}^{DA} = P_{I_s}^{DA} / \sum_{k=1}^{n} P_{I_k}^{DA}
\]

where \(P_{I_k}^{DA}\) denotes the purchase intention to buy a data commodity whose type is the same as that of \(DA\) and generated by supplier \(k\), and \(n\) is the number of this kind of supplier.
It can be estimated by the data trading KB by referring to the historic pricing records. In addition, because TIDES tends to provide demanders with higher quality data, a calibrating function that combines both data quality and purchase probability is further provided in (15),

\[
CP_{s}^{DA} = \frac{P_{s}^{DA}/Q_{s}^{DA}}{\sum_{k=1}^{n} P_{k}^{DA}/Q_{k}^{DA}}
\]  

(15)

where \(Q_{DA}^{s}\) denotes the minimal value of all quality attributes in a data commodity whose type is the same as that of DA and supplied by \(i\). Then, the supplier \(s\) can derive the expected profit according to the calibrated probability as in (16),

\[
AEP_{s}^{DA} = cost_{s}^{DA} \cdot m_{s}^{DA} \cdot CP_{s}^{DA}
\]  

(16)

Additionally, the margin that can create the most profit for \(s\) by selling \(DA\), called \(m_{s,max}^{DA}\), can be derived as follows,

\[
m_{s,max}^{DA} = \text{argmax} \frac{AEP_{s}^{DA}}{CSW_{y}} = \text{argmax} \frac{cost_{s}^{DA} \cdot m_{s}^{DA} \cdot CP_{s}^{DA}}{CSW_{y}}
\]  

(17)

Moreover, as malicious demanders could return commodities for no reason, suppliers might suffer inestimable losses. To prevent this type of badmouth attack, suppliers can set a constraint in smart contracts to exclude untrustworthy demanders.

**D. DISPUTE ARBITRATION MODEL FOR DATA TRADING**

Disputes are always issued by the demanders. Three types of disputes might occur in a data transaction: get_wrong_key, miss_key, and get_wrong_data. The TDA entities contain two functional modules, key judge and data judge, to arbitrate these disputes.

1) **KEY JUDGMENT MODEL**

After the demanders deliver their payments, they will wait for the data wrapped key and use it to generate the decryption key. However, the suppliers might fail to deliver the key or deliver a wrong key that incurs a dispute. In the miss_key dispute, if the demanders apply the blockchain payment mode to deliver their payments, the data wrapped key should be stored on blockchain. Thus, it is easy for TDA to determine the miss_key situation and then perform the refund procedure by sending a smart contract. In the get_wrong_key dispute, the demanders need to transmit the received decryption key to TDA. Then, TDA can discover whether the data wrapped key is correct and the decryption key can decrypt the data. Otherwise, TDA will activate the refund procedure.

2) **DATA JUDGMENT MODEL**

It is also possible that the received data commodity is not what the demander wants. In such a case, the demander can transmit this commodity to TDA, which will conduct the arbitration based on the information in IBS. If the argument is approved, the refund procedure will then be performed.

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**V. OPERATIONAL FLOWS AND PROTOCOLS OF TIDES**

**A. SERVICE PROVISIONING, HANDOVER AND COORDINATION SCHEME OF TIDES**

TIDES adopts the service-oriented architecture (SOA). As shown in Fig. 5(a), all entities employ a subscription-based service provisioning mechanism to realize various data trading services in a mobile environment. The service provisioning engine (SPE) is used to implement the protocols illustrated in Figs. 5(b) and (c). Each subscription queue records the requests issued from other entities for a specific service function until the subscribed services are completed or aborted, and it has a corresponding work memory to store the intermediate results generated by the functional components invoked to implement the subscribed services. These functional components may further collaborate with other functional entities to complete their missions.
The service provisioning protocol is illustrated in Fig. 5(b). For a functional entity, all the potential collaboration entities can raise their service requests to its SPE at any time. Whenever a new request is subscribed, the SPE classifies this subscription, places it into the corresponding queue, and sets the service completion event to be matched with the intermediate service execution results stored in the working memory. Subscriptions with the same requirement specification will be clustered as an aggregated subscription to deliver the service result concurrently. The SPE persistently schedules and invokes the responsible functional components to implement the subscribed services. The invoked functional components will place their execution results in the corresponding working memory. Whenever a service completion event is triggered by the content of working memory, the SPE will be notified and then collect the satisfied subscriptions from the corresponding queue. The original service requesting entities of these subscriptions will be notified to retrieve the service results from the working memory at its convenience. Obviously, according to the protocol of Fig. 5(b), the SPE can support asynchronous and multi-threaded service provisioning.

In TIDES, functional entities are deployed in both cloud centers and ME hosts, but data suppliers, demanders, or their gateways may be mobile devices. Thus, the mobility issue must be solved. Fig. 5(c) shows the service handover and coordination protocol executed by SPE to successfully deliver each service to the requesting device even if it has moved into another RAN. This protocol is the underlying mechanism of Fig. 5(b), which is automatically executed to support service handover based on the operational structure of the ETSI MEC. When service handover occurs, the SPE also needs to maintain the continued operation for the collaborations between its host edge agent and the other edge agents of different functional entities or the cloud server of the same functional entity. As shown in Fig. 5(c), the locations of mobile entities in TIDES are tracked. When a mobile device was detected moving from one RAN into another RAN, the SPE of each functional entity that provides service to this mobile device will be notified to initiate a service migration procedure. The ongoing service task and the associated context information will be transferred from the original edge agent to the current edge agent of the same functional service. The migration must include those ongoing cross-entity collaborations. To maintain consistency, the service record is also sent back to the initial service-providing edge agent.

All the following workflows are based on the service provisioning mechanism and protocols in Fig. 5.

B. DTA AND DR COMMISSION PROCESSES

When a data supplier, the demander or IoT gateway is deployed in TIDES, it will sign commission contracts with one or more DTAs and one or more DRs for future data trading needs. Fig. 6 illustrates the appointment processes as follows:

DTA Commission Process:
Step 1: The DTA/DR evaluator of the consignor (the supplier, demander or IoT gateway) surveys the DTAs that advertise their services on the bulletin of the IBS edge agent, IBS\textsuperscript{e}, in the same RAN area as the consignor.

Step 2: According to the survey result, the consignor’s DTA/DR evaluator selects some qualified candidate DTAs that their service specifications best match the consignor’s requirements for the service charge, service level, security policy, etc.

Step 3: The consignor’s DTA/DR evaluator collects the reputation information of the selected candidates from the IBS\textsuperscript{e}’s ad client reputation analyzer, excludes inappropriate candidates, ranks the remaining candidates, and finally selects one or more top-ranked candidates to negotiate the commission contract for data trading. The IBS\textsuperscript{e} can independently provide the reputation information of candidate DTAs in local data trading. If the consignor intends to proceed with global data trading, then the IBS\textsuperscript{e} will ask for the support from the cloud server, IBS\textsuperscript{c}, to provide the reputation information of candidate DTAs on global data trading.

Step 4: For each candidate DTA selected at Step 3, the consignor’s DTA/DR evaluator negotiates with the service provision negotiator of this DTA’s edge agent deployed in the same RAN as the consignor. However, the edge negotiator will work with the same DTA’s cloud negotiator to achieve a final contract agreement.

Step 5: If one or more contract agreements are achieved, the consignor’s DTA/DR evaluator signs commission contracts with the target DTAs, and then terminates this procedure. Otherwise, if there is no agreement achieved, the consignor’s DTA/DR evaluator decides to go back to Step 1 or terminate this procedure. At the consignee side, all signed contracts are stored in the profile and log DB. At the consignee side, the client DB of DTA cloud server will store all commission contracts, whereas the local client DB of
C. DATA COLLECTION AND DEPOSIT PROCESS

Fig. 7 illustrates the data collection and deposit process of a data host (a data supplier or its gateway) in TIDES.

**Step 1**: The data encryptor encrypts the acquired data set $D_i$ according to (1).

**Step 2**: The data dispatcher decides the storage scheme for the encrypted $D_i$, based on the host’s data management policy. If the private storage scheme is adopted due to high privacy concern, go to Step 3. On the other hand, if the third-party storage scheme is adopted to promote data aggregation and trading, go to Step 4.

**Step 3**: (Private storage scheme) The data dispatcher deposits the encrypted $D_i$ in the private data repository, and $DR_e$, logs the URL of $DR_e$ in the profile and log DB and then terminates this process.

**Step 4**: The data dispatcher further considers the sales policy for $D_i$. If the local sales policy is adopted, go to Step 5. Otherwise, go to Step 6.

**Step 5**: (DR assignment for edge storage scheme) The data dispatcher negotiates with those $DR_e$ edge centers that have signed a commission contract with the host, in the sequence of their ranks until the destination $DR_e$ is decided or all candidate $DR_e$s are run out. If no $DR_e$ can provide storage service for the encrypted $D_i$, the host may have the following alternative decisions: (a) change to the private storage scheme and go back to Step 3, (b) re-invoke the DR commission process to delegate a new DR and then repeat this step. During the negotiation, the candidate DR’s edge center in the same RAN as the data host will play the role of the service proxy between the host and the candidate cloud DR.

Each candidate $DR_e$ performs the following actions.

**Step 5a**: The data dispatcher inquires the $DR_e$’s repository manager of the service availability. If the repository manager admits this service request, go to Step 5b. Otherwise, go back to Step 5 to determine the next candidate $DR_e$.

**Step 5b**: The data dispatcher submits the profile of $D_i$ to the local management DB of $DR_e$. A copy of the profile will also be saved in the global management DB of the same DR’s cloud center ($DR_c$).

**Step 5c**: The data dispatcher delivers the encrypted $D_i$ to the IoT data store of $DR_e$, logs the URL of $DR_e$ in the profile and log DB, and then terminates this process.

**Step 6**: (DR assignment for the cloud storage scheme) The assignment process is similar to Step 5, but those commissioned $DR_c$ cloud centers participate in negotiation. If no $DR_c$ can provide storage services for $D_i$, then the host may have the following alternative decisions: (a) change to the edge storage scheme and go back to Step 5, (b) change to the private storage scheme and go back to Step 3, (c) re-invoking the DR commission process to delegate a new DR and then repeat this step. Each candidate $DR_c$ performs the same actions on the cloud side as $DR_e$ in Steps 5a-c and invokes the repository manager of $DR_c$ as a proxy.

D. SMART CONTRACT CONSTRUCTION PROCESS

Fig. 8 illustrates the process by which the supplier’s smart contract constructor executes to establish the smart contract, as shown in Fig. 3, for data set $D_i$.

**Step 1**: (Activate $DTA_i$) Negotiate with the commissioned DTAs in the sequence of their ranks until the destination DTA, say $DTA_i$, is decided or all candidate DTAs are run out. If a $DTA_i$ is available, activate it and then go to the next step. Otherwise, if no DTA is available, the supplier either waits until some DTA is available...
Employ the DTA\textsuperscript{i}'s data price analyzer to obtain the reference price of $D_i$ according to the aforementioned data pricing model. If the local sales policy for $D_i$ is adopted, the reference price is estimated with the parameter values of the data pricing model from the DTA\textsuperscript{i}'s data trading KB. However, if the global sales policy for $D_i$ is adopted, then the inquiry for the reference price is forwarded to the DTA\textsuperscript{i}'s data price analyzer which estimates the reference price of $D_i$ by referring to the DTA\textsuperscript{i}'s data trading KB.

**Step 3:** Based on the reference price of $D_i$, decide the final price of $D_i$ to be announced in the contract according to the supplier’s sales strategies and experiences that are accumulated in the profile and log DB.

**Step 4:** Fills the values of all fields in the smart contract of $D_i$ based on the information recorded in the supplier’s profile and log DB and the execution results achieved at previous steps.

**Step 5:** Activate the smart contract deployment process to compile the complete smart contract of $D_i$.

**Step 6:** (optional) Activate the smart contract advertising process for the smart contract of $D_i$.

**Step 7:** Store the smart contract and advertisement of $D_i$ into the supplier’s profile and log DB and then terminate this process.

The DTA\textsuperscript{i}'s data trading KB is continuously updated by its local KB maintainer based on the analytical results of the smart contract announcements on the IBS\textsuperscript{c}, the data trading records in the DTB local chain (DTB\textsuperscript{c}), and the local dispute arbitration records. The maintainer also refers to the knowledge of interest from the DTA\textsuperscript{i}'s data trading KB to fine tune the local KB. DTA\textsuperscript{i} applies the same mechanism for maintaining its global data trading KB by referring to the smart contract announcements on IBS\textsuperscript{c}, the data trading records in the DTB main chain (DTB\textsuperscript{e}), and the global dispute arbitration record.

### E. SMART CONTRACT DEPLOYMENT PROCESS

Fig. 9 shows the details of this process. It is a subprocess of Fig. 8. To initiate this process, the supplier’s smart contract constructor sends a contract deployment request with the trading information of $D_i$ to the commissioned DTA\textsuperscript{i}.

**Step 1:** DTA\textsuperscript{i} reviews the supplier’s request; if a global contract deployment is requested, go to Step 6. Otherwise, go to the next step.

**Step 2:** The DTA\textsuperscript{i}’s contract compiler generates the bytecode and ABI according to the trading information of $D_i$, and sends them to the contract deployer.

**Step 3:** DTB\textsuperscript{e} responds the contract deployer with a contract ID.

**Step 4:** The contract deployer deploys the bytecode of the $D_i$’s local smart contract to DTB\textsuperscript{e}.

**Step 5:** The contract deployer sends the complete local smart contract of $D_i$ back to the supplier’s smart contract constructor, and then terminates this process.

**Step 6:** The trading information of $D_i$ is sent to the DTA\textsuperscript{i}’s contract compiler through DTA\textsuperscript{i}. Then, the following actions used to generate the global smart contract of $D_i$ are the same as those described in Steps 2~5. However, the smart contract of $D_i$ is deployed in DTB\textsuperscript{e}.

### F. SMART CONTRACT ADVERTISING PROCESS

Fig. 10 shows the details of this process. It is a subprocess of Fig. 8. Initially, the supplier’s smart contract constructor sends an advertisement request with the smart contract of $D_i$ to the commissioned DTA\textsuperscript{i}.

**Step 1:** DTA\textsuperscript{i} reviews the supplier’s request; if a global advertisement is requested, go to Step 6. Otherwise, go to the next step.

**Step 2:** The DTA\textsuperscript{i}’s advertisement deployer sends an advertisement request with the smart contract of $D_i$ to the IBS\textsuperscript{c}’s ad planner.

**Step 3:** The IBS\textsuperscript{c}’s ad planner evaluates the $D_i$’s smart contract and creates an advertisement for $D_i$ by referring to the ad KB which is maintained by the ad performance evaluator according to the analytical results for the trading records of the smart contracts in DTB\textsuperscript{e}.

**Step 4:** The IBS\textsuperscript{c}’s ad planner gets approval for the advertisement of $D_i$ from the DTA\textsuperscript{i}’s advertisement deployer.

**Step 5:** The IBS\textsuperscript{c}’s ad planner announces the advertisement of $D_i$ on the ad bulletin and logs it in the ad client DB. Then, this process is terminated.

**Step 6:** The $D_i$’s smart contract is sent to the DTA\textsuperscript{i}’s advertisement deployer through DTA\textsuperscript{i}. Then, the following actions to generate the global advertisement of $D_i$ are
the same as those at Steps 2∼5. However, the advertisement of $D_i$ is announced on $IBSe$’s the ad bulletin.

G. TRUST-AWARE DATA TRADING PROCESS

Fig. 11 illustrates the entire data trading flow over TIDES, which can be divided into the qualified contract sifting subprocess and the trading approval, payment and data delivery subprocess. When a demander is going to purchase data set $D_i$, it activates a $DTA_{id}^e$ by a procedure similar to Step 1 of the smart contract construction process, and then the two subprocesses are executed as follows.

1) QUALIFIED CONTRACT SIFTING

Step 1: The demander’s contract dealer sends the data purchase requirements for $D_i$ to the activated $DTA_{id}^e$.

Step 2: The $DTA_{id}^e$’s contract mediator reviews the demander’s requirements; if global trading is requested, then go to Step 6. Otherwise, go to the next step.

Step 3: The $DTA_{id}^e$’s data value evaluator collects the data contract advertisements that meet the demander’s requirements from the local $IBSe$, and evaluates the collected data trading contracts based on the data value evaluation model proposed in Section IV.C. The evaluation results are then sent to the contract mediator as a reference for deciding the qualified data contracts to proceed with data transactions.

Step 4: The $DTA_{id}^e$’s trust evaluator employs the model proposed in Section IV.B to estimate the suppliers’ trustworthiness of the contracts collected at Step 3. The evaluation results are then sent to the contract mediator as a reference for deciding the qualified data contracts to proceed with data transaction.

Step 5: According to the evaluation results from Steps 3 and 4, the $DTA_{id}^e$’s contract mediator abandons the contracts with untrustworthy suppliers, and then ranks the remaining contracts according to their valuations. If at least one qualified contract exists, then go to the trading approval subprocess. Otherwise, the contract mediator notifies the demander’s contract dealer for no qualified data contract, and goes to Step 9.

Step 6,7,8: Respectively similar to Steps 3, 4 and 5, but executed by the cloud-side entities and referring to cloud-side information.

Step 9: The demander’s contract dealer makes one of the following two decisions:

1) Abort the data purchase request and terminate the data trading process.
2) Change the data purchase policy from local trading to global trading and go to Step 6 (this decision is considered only when the previous step is Step 5).

2) TRADING APPROVAL, PAYMENT AND DATA DELIVERY

The following procedure describes the operational flow for local data trading. Global data trading has a similar operational flow. This subprocess is executed for each of the qualified contracts according to their ranks decided at the previous subprocess until the data purchase request is approved by a supplier or declined by all suppliers of the qualified contracts.

Step 1: The $DTA_{id}^e$’s contract mediator obtains the contact window $DTA_{id}^e$ from the advertisement of the target contract.

Step 2: The $DTA_{id}^e$’s contract mediator notifies the $DTA_{id}^e$’s contract mediator for the purchase request for $D_i$.

Step 3: The $DTA_{id}^e$’s trust evaluator employs the evaluation model proposed in Section IV.B to estimate the demander’s trustworthiness on data trading.

Step 4: The $DTA_{id}^e$’s contract mediator notifies the supplier for the evaluation result obtained in Step 3.

Step 5: According to the evaluation result, the supplier’s contract manager approves or declines the request, and then notifies $DTA_{id}^e$ of the decision.
Step 6: The DTaSi’s contract mediator notifies DTaSi of the supplier’s decision. Then, the DTaSi’s contract mediator forwards this decision to the demander.

Step 7: If the request is declined, the demander terminates this process; otherwise, it executes one of the following two actions:
1. If the blockchain payment mode is adopted, the demander’s contract dealer activates the corresponding smart contract in DTbSi to pay for purchasing Di. Then, DTbSi notifies the supplier with a payment completion message.
2. If the off-chain payment mode is adopted, then the demander’s contract dealer contacts the supplier’s contract manager to complete the payment directly.

Step 8: After receiving the payment completion message, the supplier’s contract manager generates the data wrapped key of Di according to (2). Then, if the blockchain payment mode is adopted, the data wrapped key will be updated on blockchain by smart contract; otherwise, the data wrapped key will be sent to the demander through the contract mediators of DTaSi and DTaSi. At the same time, the private or third-party DR that stores Di is instructed under the supplier to deliver the encrypted Di to the demander.

Step 9: The demander’s data decryptor decrypts the received Di by applying (3) and (4) with the supplier’s public key announced in the dealt smart contract.

Step 10: The demander’s contract dealer judges whether the decrypted Di is the desired ones. If yes, this process is terminated. Otherwise, the demander’s dispute arbitration negotiator will apply for the dispute arbitration process through TDAe to refund the payment.

H. DISPUTE ARBITRATION PROCESS

Fig. 12 illustrates the details of this process as a subprocess of the trust-aware data trading process. The following procedure describes only the operational flow for local data trading. Global data trading has a similar operational flow.

Step 1: The demander’s dispute arbitration initiator asks its DTAid to file an arbitration request for the trading of Di.

Step 2: The DTAid’s contract mediator files an arbitration request to TDAe with related evidence.

Step 3: The TDAe’s arbitration processor notifies the supplier of Di of the arbitration request through DTAid, and collects the other evidence from IBSi and DTbSi.

Step 4: The TDAe’s arbitration processor activates the key judge and data judge and gives the collected evidence.

Step 5: The TDAe’s key judge and data judge employ the judgment models proposed in Section IV.D to arbitrate the dispute, and then reply to the arbitration processor.

Step 6: According to the received judgment results, the TDAe’s arbitration processor makes the final arbitration for the dispute, records the result in the arbitration result DB, and notifies the demander and supplier through DTaSi and DTaSi.

Step 7: After receiving the arbitration result, the demander and the supplier must proceed to the arbitration result handling procedure as follows:
1. If the dispute does not stand, the trading of Di is reserved.
2. If the miss_key or get_wrong_key dispute stands, the demander can ask the supplier to resend the data wrapped key or refund the payment.
3. If the get_wrong_data dispute stands, the supplier refunds the payment.

VI. SIMULATION

A. SIMULATION SETTINGS

TIDES has been implemented in blade servers equipped with Intel Xeon E5-2620 2.1 GHz processors with 32 cores and 4 cores to simulate the operational environments of the cloud servers and MEC hosts, respectively. In all simulations, both the main chain and local chain of DTB are implemented by Ethereum technology; the former is executed in cloud servers and the latter in MEC hosts. The simulation environment is composed of 10 RAN areas, and each area contains ten ME hosts and several IoT gateways. Each area generates 50 local transactions per second for local data, and only ten percent of these local data will be further queried for global usage by default. Referring to the setting of the Ethereum public chain [28], each transaction requires approximately 320 bytes of storage, and each block contains 150 transactions at most. Additionally, Geth 1.6 is utilized to implement the Ethereum client. Twoi is applied as the trading unit. Twoi is a denomination of ether, ETH, which is the crypto-coin applied on the Ethereum network, and 1 Twoi = 10^-6 Eth.
Two types of simulations are performed in the paper, including the system performance simulation and the trading efficiency simulation. The system performance simulation shows the improvement of TIDES in terms of trading time and storage costs. The trading efficiency simulation demonstrates that suppliers in TIDES can make higher profit. In the meantime, the data quality of purchased data and pricing efficiency can also be improved. Additionally, when the environment is malicious, TIDES can make more successful transactions than other pricing models because TIDES considers the trustworthiness of both demanders and suppliers.

B. SIMULATION FOR SYSTEM PERFORMANCE

In the following simulation, assume that each area acquires data to trade lasting for 140 seconds, respectively. Different from the Ethereum public chain, TIDES applies a hierarchical blockchain in which only the global transactions need to be carried out through the main chain and delivered around the world.

1) TRADING TIME

Generally, trading time is the most important criterion for performance evaluation. A smaller trading time means that the demanders can obtain their desired data commodities more quickly and that more transactions can be made during the same time period. The trading time includes the time to perform PoW operation and the time to deliver block to all full nodes. As estimated in [28], the Ethereum public chain spends 2 seconds on the PoW operation and 12 seconds on global block delivery. Thus, in the system performance simulation, each global transaction takes approximately 14 seconds. For a local transaction, 2 seconds are also assumed to be spent in the PoW operation and 1 second is spent on local block delivery.

The total trading time indicates that the time to complete all global transactions, which can be regarded as the capability of a trading system. As shown in Fig. 13, compared to the Ethereum public chain that spreads all transactions to all full nodes around the world even though most data transactions are done locally, the total trading time of the TIDES hierarchical blockchain is much smaller. It can be discovered that

![FIGURE 13. Comparison of total trading time under different numbers of areas.](image)

Fig. 14 shows the total trading time with respect to different global transaction ratios from 10% to 100%. Although the total trading time of the TIDES hierarchical blockchain grows and becomes close to the Ethereum public chain when the global transaction ratio increases, it is still much less than that of the Ethereum public chain in most cases. In practice, most transactions are made locally.

2) STORAGE COST

For an IoT data trading system, the storage cost is mainly spent in recording the IoT data transactions. Since most data transactions are made locally, it is a waste to log all transactions in a global chain. Moreover, as the number of RAN areas increases, more transactions are made, which increases the difference between the hierarchical blockchain and the Ethereum public chain.

![FIGURE 14. Comparison of total trading time under different global transaction ratios.](image)

![FIGURE 15. Comparison of storage costs for different numbers of areas.](image)

Fig. 15 shows the total storage cost for different numbers of areas. It can be discovered that the Ethereum public chain can easily become a performance bottleneck because too many transactions are required to be stored in global chain. Moreover, as the number of RAN areas increases, more transactions are made, which increases the difference between the hierarchical blockchain and the Ethereum public chain.

The enormous storage cost will severely increase the maintenance expense, which might lead to system monopolization. As a result, the reliability of the data trading system will be...
compromised. Thus, the proposed hierarchical blockchain is more applicable as an IoT data trading system.

C. SIMULATION FOR TRADING EFFICIENCY

This simulation evaluates the data trading efficiency of various pricing models under two different settings for the trading environment, including an ideal one and a malicious one. The former indicates that all participants are honest and the latter assumes that malicious suppliers exist. In the simulation, five suppliers with different pricing models are used to provide data commodities continuously. The data quality is randomly set as low, medium or high. The costs of data commodities are set between 500 and 50,000 based on their data quality. The acceptable price of the demanders is set between 1,000 and 150,000 based on the quality of their desired data. The purchase intention is assumed to be related to the C-P ratio of data commodities.

1) TRADING IN AN IDEAL ENVIRONMENT

In this simulation, all suppliers are assumed to be honest. The five suppliers respectively apply the TIDES’s pricing model, the cost model [15] with a static margin, the RIDES’s [9] and MGA’s [18] pricing models which ignore the market situation, and the conventional non-cooperative game model [20] which refers to the information of the competitors. For the last pricing model, if the supplier fails to reach a deal in this round, it will decrease its margin compared with the margin of a successful competitor.

As shown in Fig. 16, TIDES always obtains the higher total profit because it takes the market situation into consideration. The conventional non-cooperative game model obtains the least profit as it continuously decreases its margin.

As shown in Fig. 18, although more than half the transactions are performed by the non-cooperative game model, its total profit is not as high as that of TIDES. By contrast, TIDES performs the second most transactions and obtains the most profit.

Moreover, the pricing efficiency denotes the profit obtained from per pricing effort, which is achieved by dividing the profit by the time spent on pricing. As shown in Fig. 19, TIDES has the best pricing efficiency although it takes some effort to derive an appropriate price. The cost model has the second best pricing efficiency due to its simplicity. Although RIDES is slightly faster than MGA, the latter makes more profit and thus has better pricing efficiency than RIDES. The non-cooperative game model has worse performance and the worst profit leading to the worst pricing efficiency.

In the simulation, although suppliers randomly generate data of three different qualities, demanders also randomly define a minimal quality limit. Hence, data of higher quality will be purchased more than that of lower quality. As shown in Fig. 20, demanders in TIDES purchase more high-quality data (55.4%) and less low-quality data (9.5%) than other competitors in a timely manner. Even so, TIDES still achieves the highest total profit. For the non-cooperative game model, the profit in a single transaction decreases steadily, which indicates that it falls into the price war.

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In this simulation, the trustworthiness of a supplier indicates the probability that this supplier is honest. As shown in Fig. 21, when the average trustworthiness of the suppliers is 90, which means that the trading environment is friendly, the trustworthiness evaluation model can decrease by 5% of the trading failure rate. As the average trustworthiness of the suppliers decreases, which indicates that the trading environment becomes unreliable, the trustworthiness evaluation model can reduce the trading failure rate by approximately 40%. Apparently, the trustworthiness evaluation mechanism significantly improves trading reliability. Therefore, the demanders in TIDES are more likely to obtain what they want.

VII. CONCLUSION

This paper proposes and further implements TIDES to provide users an automatic, reliable and intelligent IoT data trading environment. Further with blockchain technology and smart contracts, IoT data trading can be automatically performed. The trustworthiness evaluation model can eliminate malicious suppliers and demanders to ensure data transactions. In addition, the client-centric data value evaluation model and game-theory-based pricing model help the demanders to obtain higher quality data commodities at an acceptable price and the suppliers to obtain the highest profits. With the hierarchical blockchain, the system performance is increased, and the storage cost is greatly reduced. The MEC technology also makes TIDES satisfy the mobility requirement. The simulation results have demonstrated that TIDES ensures the efficiency, intelligence and reliability of IoT data trading.

APPENDIX

Abbreviations in this paper are summarized in TABLE 1.
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VOLUME 8, 2020