Energy-aware Demand Selection and Allocation for Real-time IoT Data Trading

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Abstract—Personal data is a new economic asset that individuals can trade to generate revenue on the emerging data marketplaces. This paper introduces a decentralized marketplace for trading personal sensing data, generated by resource-constrained IoT devices in real-time. To design such a marketplace, we consider both computing and economic aspects. The computing approach focuses on creating a blockchain-based decentralized marketplace that ensures the integrity of trade agreements. We leverage smart contracts to guarantee that the participants automatically conform to the terms of the agreements without involving a mediator. The economic approach maximizes the marketplace participant’s utility to improve the sustainability and usability of the marketplace. To this end, we present a blockchain framework underpinned by an Energy-Aware Demand Selection and Allocation (EDSA) mechanism that optimizes the revenue for the seller and fulfills the buyer’s demands. We use a normalized revenue-based greedy algorithm for solving the EDSA problem. Moreover, we present a proof-of-concept implementation of the blockchain framework in Ethereum. Through extensive simulations, we separately evaluate the impact of buyer’s demand on the battery drainage of the IoT devices under different scenarios. We observe that increasing battery capacity for IoT devices on the seller end is more strongly related to revenue generation than increasing the number of devices.

Index Terms—Blockchain, smart contract, optimization, energy consumption, data marketplace, IoT, economics

I. INTRODUCTION

The volume of sensing data generated by personal IoT devices is overwhelming. It is expected that in 2025, 79.4 zettabytes of IoT data will be generated globally [1]. However, this data remains heavily under-utilized mainly due to the lack of incentives and data sharing mechanisms. To address these issues, the notion of a data marketplace has been proposed. A data marketplace facilitates a seller to market their data to potential buyers.

Conventional centralized approaches based on the client-server model [2], [3], are built around a trusted third party which raises issues such as single point of failure, lack of scalability and the need for expensive infrastructure. Recently proposed, decentralized data marketplaces based on blockchain technology [4] have gained popularity to overcome the aforementioned problems by distributing the computation needs across multiple nodes. One major drawback of both approaches are that they ignore the economic aspects that are necessary to ensure wider adoption and usability and thus, the commercial success of such systems. Existing work focusing on economic aspects adopted incentive mechanisms based on pricing. For instance, [5] explored the use of blockchain technology and smart contracts to remove the need for centralized trust and identified viable boundaries for the prices of digital assets, which make the trading infrastructure economically sustainable. [6] studied the problem of revenue maximization in IoT data markets and used pricing mechanisms under different market settings where either one type of buyer exists, different types of buyers coexist or buyers have bounded rationality. These pricing strategies can motivate users to contribute their data. However, to guarantee the long-term engagement of participants, an economic model is required that analyzes the trade-off between maximizing the seller’s and the buyer’s utility.

Designing and developing a data marketplace model requires a holistic approach driven by both computing and economics to ensure sustainability, usability and wider adoption of the marketplace for buying and selling IoT data [7]. Economic aspects include maximizing the utility of the users while computing aspects include key marketplace functionalities such as data discovery, negotiation, agreement formation, settlements, data delivery and privacy mechanisms [8]. In this paper, we focus on both economic and computing aspects to develop a holistic framework that addresses the following issues related to data marketplaces:

1) Agreement Integrity - The majority of blockchain based proposals [9], [10] follow a hybrid approach where a companion blockchain offers services such as access control policies or product catalog listings using smart contracts. Different from these approaches, this paper explores the computation and automation capability of smart contracts [4]. Smart contracts are small pieces of self-executing code that reside in the blockchain network for automatically enforcing the terms of agreements between any two parties. In this work, we use smart contracts to manage the agreement life cycle and automatically establish a channel for trading and settling disputes among the parties. A smart contract-based agreement framework for data marketplaces ensures the integrity of an agreement, non-repudiation of the owners, improves reliability and allows regulatory bodies to (selectively) monitor trades.

2) Impact of resource-constrained IoT devices on the user’s utility - A trading infrastructure is economically sustainable when the seller and buyer utility are satisfied [7]. The utility of the seller depends on the revenue generated from data trading while that of the buyer depends on getting quality data for the desired rate and duration. However, IoT devices are restricted
in their capabilities. These devices derive their energy from batteries or external sources using harvesters. Recharging or using harvesting techniques can prolong the battery lifetime but typically, the available energy is insufficient to stream continuous data to multiple buyers in real-time [11]. Since there is an energy cost associated with continuously sensing and transmitting data in real-time, a seller has to make an optimal decision based on the current residual energy and capabilities of the devices. In other words, a seller needs to identify the number of buyer demands that he can serve so that both the seller and the buyers achieve their desired goal of maximizing their utility.

Our paper makes the following contributions to achieve the aforementioned aims:

- We develop a blockchain enabled framework for IoT data marketplace for trading personal sensing data from battery-operated IoT devices in real-time. We present details of the framework including architectural design, actors relations, and interactions among participating parties.
- We leverage smart contracts for the formation and management of service level agreements between sellers and buyers for data trading, for automating the calculation of reputation scores, and for computing the price of the data type. We present details of our smart contracts and their interaction to achieve data trading. A proof-of-concept implementation on Ethereum is developed and evaluated.
- We formulate the Energy-aware Demand Selection and Allocation (EDSA) optimization problem to maximize the seller’s revenue by taking into account the resource-constrained nature of IoT devices in real-time data trading. We use a greedy heuristic algorithm to solve the EDSA problem. Furthermore, we investigate the effect of the buyers demand on the power consumption of the seller’s devices and evaluated the selection and allocation of buyer’s demands to maximize the seller’s revenue.

The rest of this paper is organized as follows. In Section II, we survey the related research. Section III presents an overview of the marketplace. In Section IV, we present the details of smart contracts followed by the integer linear formulation of EDSA in Section V. Proof of concept implementation and evaluations are presented in Section VI, and Section VII concludes the paper.

II. RELATED WORK

In this section, we discuss existing works which can be broadly categorized into two groups: blockchain-based data marketplace frameworks and task allocation based on optimization.

Blockchain-based Data marketplace frameworks - Various related works exist that contribute to the advancement of IoT based marketplace design. We provide an overview of these works and highlight the unique approach of our work in contrast to the state-of-the-art.

PrivacyGuard is proposed in [12] to enable the data owners to have control over the access and use of their private data. They leverage data brokers for improved scalability. Smart contracts are used to encode the access and usage policies, while the blockchain records data transactions. Smart contract functions are split into control operations and data operations to enable complex and confidential operations on private data. However, the proposed execution of complex data operations in a confidential manner for providing secure off-chain execution requires specific hardware, i.e., Intel SGX, which limits its applicability on different platforms. [13] presents a centralized marketplace called HERMES which relies on well known cryptographic primitives to preserve the privacy of the transacting parties. The marketplace acts as a metadata catalog and provides dispute resolution mechanisms. They use IOTA as a data storage and streaming medium. However, in addition to suffering from the drawback of centralization, transparency and fairness of transactions among the entities were not considered. In [14], smart contracts are used to set the conditions and rules for automating the trade of IoT data. An MQTT broker (which uses publish-subscribe network protocol) hosted in the cloud aggregates the IoT data and authenticates buyers based on the access tokens issued by the smart contracts. Similarly, in [15], the authors use smart contracts for handling access control policies and evaluating access requests. However, data owners store their data off-chain in a remote storage provider. In both cases, data sellers advertise their offers to the smart contract while data buyers can browse all available offers by querying the blockchain. The difference between the two is that the former approach uses MQTT for real-time streaming of data, while in the latter approach, the framework uses data sharing schemes based on Access Control Lists (ACLs) and prefix encryption from storage. With the expected increase in the number of IoT devices, advertising offers on the blockchain is not a scalable solution. Similar to our approach, [16], [17] uses blockchain to record agreements but neither provide any details of how smart contracts are employed to automate the execution flow of the agreements.

Task allocation based on optimization - The seller’s revenue in a marketplace is affected by the resource usage of his IoT devices. The available resources on an IoT device are often not sufficient to fulfill a given set of buyers’ demands. Thus, demand selection and allocation are essential for fair distribution of demand, reducing energy consumption and increasing revenue generation. In this section, we survey some of the approaches that address the user’s task allocation to seller’s devices subject to device’s limited resource.

In [18], authors considered an IoT device equipped with multiple heterogeneous network interfaces to which services need to be assigned. The paper presents a mixed-integer linear programming formulation of the Service to-Interface Assignment (SIA) problem, which aims to minimize the total cost of utilizing the interfaces’ resources while satisfying the services’ requirements. The authors developed an algorithm to approximate the optimal solution of the SIA problem with the goal of serving all the services. While, in our case, we are interested in the selection of a subset of demand. In
resources. We considered these guidelines while designing our marketplace framework.

As our extensive literature survey reveals, there is a need for the design of a marketplace, which considers both economic and computing aspects of trading IoT data from resource-constrained IoT devices. In the next section, we present an overview of the architectural design and high-level interaction of the actors.

III. OVERVIEW OF MARKETPLACE

In this section, we present the system overview and architectural design for trading IoT data in real-time in an automated and decentralized manner. As discussed in section I, the two issues related to agreement integrity and real-time data trading from resource-constrained IoT devices can be tackled by incorporating the following two requirements: 1) The agreements should execute automatically when pre-defined conditions are met, and 2) the demands should be selected in a way that the seller can fulfill all of the potential demands on a real-time basis. Blockchain technology satisfies the first requirement. In our work, we opted for the Ethereum public blockchain which supports smart contracts ensuring that participants’ behaviors automatically conform to the terms of the agreements. To address the second requirement, we devise mechanisms to maximize the user’s utility by establishing real-time data trading from the resource-constrained IoT devices. The primary users of our system are sellers and buyers. A seller’s utility is measured by the generated income, while a buyer’s utility is measured by the satisfaction of its demands.

To achieve this aim, our framework proposes a blockchain integrated optimization module that is organized into four layers: physical, blockchain, off-chain and application with supporting components. In the following subsections, we will briefly describe the major components of our multi-layered framework and its underlying key techniques. Due to space limitations, the technical details for implementation of each layer are beyond the scope of this paper and thus are omitted.

A. Multi-layered blockchain framework

Our data marketplace framework has four layers: Physical, off-chain, Blockchain and application stacked as shown in Fig. 1.

Fig. 1. Multi-layered Blockchain Framework.

[19] presents a systematic literature review of various resource allocation methods in the IoT context and discusses their advantages and disadvantages. The paper concludes that collaboration of resource modeling, allocation, and monitoring is necessary to enable proper and continuous operation of IoT resources. We considered these guidelines while designing our marketplace framework.

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ized revenue-based algorithm to solve the EDSA problem. These mechanisms are explained and formulated separately in Section V.

- **Negotiation** - A seller begins the negotiation using Contract Net Protocol [21] with the selected buyers by generating an initial offer. Based on the application requirements and the budget, the buyer either accepts the proposal or offers a counter-proposal. This process continues until an agreement is reached. The relevant information such as starting time of negotiation, number of proposals, end time of negotiation, negotiation terms, and negotiated price are recorded in the agreement.

- **Transmission and metering** - Once the agreement is signed, the actual data transfer commences off-chain via a secure TCP connection established between the buyer and the seller. The seller and buyer also maintain the count of the transferred data samples using the metering sub-component which is used in the settlement.

3. Blockchain layer - We adopted the design of this layer from [22]. There are four different smart contracts, namely, data subscription contract, register contract, pricing contract and rating contract which interact with each other to automate the execution flow of the agreement. The negotiated terms are enforced automatically by the smart contracts, eliminating the need for any intermediaries. These smart contracts are invoked by the write transactions at different stages of the data trading process either from the off-chain or the application components. The detail of the smart contracts, their methods and associated transactions are presented in detail in Section IV.

The following subsections discuss the high-level design aspects, main actors, their roles and the interactions between them.

**B. Actors and their interactions**

Our marketplace model involves three actors: (1) IoT device owners who are interested in selling the sensing data from their devices assume the role of sellers, (2) data consumers who are interested in purchasing real-time sensing data assume the role of buyers, and (3) broker takes on the role of a facilitator.

- **Seller** - The primary motivation of the seller is to generate sustainable income. To achieve this, a seller uses two strategies. Firstly, a seller tries to maximize his revenue by using his available resources as efficiently as possible. Secondly, a seller can attract buyers by offering IoT data with high quality or possessing a high risk of privacy violation [23] as add-on features. The seller posts the offerings to the facilitator as metadata. The metadata, which is updated by the seller when required, consists of information such as public identifier (i.e., changeable public key) to anonymize the identity of the seller, list of IoT devices owned, geographical co-ordinates associated with the sensing data, temporal context of the data which can be static or dynamic and data usage license which defines the appropriate use of the data and also includes terms for restrictions of reselling of the data. In this work, we do not address the problem associated with reselling the data by unauthorized agents. Digital watermarking techniques [24] can be used to solve this problem.

- **Buyer** - The primary motivation of a buyer is to maximize his utility by satisfying his demands. The buyer’s requirements are classified into two categories: context-based requirements such as data type, location, temporal context, and seller’s rating and quantitative-based requirements such as data quality, sampling interval and duration. The difference between the two is that the latter depends on the battery availability of the seller’s devices while the former does not. Buyer’s quantitative requirements directly impacts the seller’s battery consumption. The existing techniques [26] for improving power consumption of IoT devices usually compromise data quality for energy efficiency. High quality (high accuracy and frequency, low latency) usually consumes more energy. For instance - different localization techniques such as GPS, Assisted GPS, Wifi positioning system (WPS) or Cell-ID can be used to acquire location data of a seller. The positioning approach which provides the most accurate location information, consumes more power as shown in the Table I.

Similarly, when the sensor of an IoT device is working at a low sampling interval and for a longer duration, it will consequently imposes a heavy workload on different components (i.e., processor, network, storage and sensors) of the device. This heavy workload drains the battery rapidly, impacting the seller’s utility. As an example, if a smart phone owner sells its location data by sending frequent (smaller sampling interval) location data for a long duration, its phone battery depletes quickly. This degrades the smart phone experience and impacts other buyers’ demands with whom the seller has already made an agreement. On the other hand, if a low data rate setting is applied, it may yield unsatisfactory data quality which impacts the buyers’ utility. Thus, it is vital to find a solution that balances the power consumption of a seller’s device and buyers’ demands while also maximizing the participants’ utility for creating a sustainable marketplace.

- **Facilitator** - An important challenge in implementing a generalized blockchain solution for a marketplace is to deal with scale. To address the problem of scalability, we leverage geographically distributed facilitators that are interconnected in a P2P network and forming an overlay network spanning the entire globe. Each facilitator is expected to oversee a particular service area/geographic region. The facilitators are synchronized for improving the robustness of the marketplace. We assume that the facilitator is a trusted and highly resourced entity whose motivation is to receive incentives in return for its service.

The high-level interactions among the actors are illustrated in Fig. 2. Each facilitator maintains the catalog of offerings and

| Localization Techniques | Power usage | Accuracy |
|--------------------------|-------------|----------|
| Inbuilt GPS receiver     | high        | 20ft     |
| AGPS                     | medium      | 200ft    |
| Cell-ID or WPS           | low         | 5300ft   |
demands that belong to his service areas. All the other actors (i.e., sellers and buyers) must register with a facilitator that is nearest to their geographical location and create a profile. A facilitator receives a list of demands from buyers and a set of offerings from sellers. It matches the service offerings and demands based on the criteria specified by both the actors, such as location, data types, budget-pricing using a discovery and selection algorithm proposed in [27]. Next, the facilitator creates a list of potentially matching buyers and sends it to all the identified sellers. Note that, quantitative-based requirements depend on the battery availability, a fast-changing factor, of the seller’s device. To avoid network overheads associated with the seller updating the facilitator with the current battery level of his devices, a facilitator performs matching based only on the context-based requirements of the buyer’s demand. Since demand is sent to multiple sellers, there is no negative implication of using stale energy information in the seller’s device.

IV. COMPUTING ASPECTS: SMART CONTRACTS

The smart contracts encoded with terms of the agreement are compiled into bytecode and deployed on the blockchain with unique addresses that can be invoked using transactions or messages. Transactions are used to update or modify the state of smart contracts. A smart contract can consist of several functions. So, the application binary interface (ABI) is required to specify which function in the contract to invoke along with the address of the contract. Agreement details, participant’s ratings, and data prices are recorded in blockchain in a transparent, secure, efficient, and automated way using data subscription, rating, and pricing contracts, respectively. Fig. 3 depicts how these contracts accomplish the various phases of data trading. The ABIs and the transaction details for each contract are given in detail below.

**Data Subscription Contract (DSC)**: The terms of agreements, including the negotiated terms, are encoded in DSC. Each seller-buyer pair have a single DSC to provide flexibility and customization based on their specifications. The DSC maintains the list of subscriptions which includes subscription id, seller id, buyer id, device id, data type, start time, periodicity, duration, quality score (QS), privacy risk score (RS), total cost, payment granularity, transaction status, negotiation information. Device id is the hash of device H/W serial number to ensure that the seller’s claim of owning the device is correct and the information is stored in hash form for the sake of privacy. The DSC provides the following ABIs to manage the subscription list.

- **subscriptionAdd():** This method adds a new subscription request to the existing subscription list. The transaction $T_{\text{add}}(ID_b|\text{Hash}_d|\text{Sig}_s|\text{PU}_s)$ can only be issued by the seller. $ID_b$ is the buyer’s id and $\text{Hash}_d$ is the hash of the subscription details. $\text{Sig}_s$ and $\text{PU}_s$ are the signature and public key of seller, respectively.

- **subscriptionInfo():** This ABI receives the subscription id and returns the corresponding subscription detail. The transaction $T_{\text{info}}(\text{SID}|\text{Sig}|\text{PU})$ can be initiated by either of the concerned parties where $\text{SID}$ is the subscription id, $\text{Sig}$ and $\text{PU}$ are the signature and public key of either seller or buyer.

- **subscriptionStart():** Subscription is started by the seller at the subscription start time using $T_{\text{start}}(\text{SID}|\text{Sig}|\text{PU})$.

- **subscriptionSettlement():** This ABI is executed by $T_{\text{settle}}(\text{SID}|\text{D}_{\text{count}}|\text{Sig}|\text{PU})$ where $D_{\text{count}}$ is a positive integer while $F$ is a real number in $(0,1)$. Both seller and buyer are required to submit the data count $D_{\text{count}}$ and provide feedback $F$ to the other actor based on his experience. This ABI performs settlement by comparing the received data counts and takes the following action based on the situation. Case 1: If data counts from both buyer and seller are equal, i.e., no conflicts exist, an invoice is generated for the buyer and payment is released to the seller. Case 2: Otherwise, in a dispute situation, the actor with the higher reputation score, managed by a rating contract, is trusted.

- **subscriptionDelete():** On completion of the subscription, $T_{\text{del}}(\text{SID}|\text{Sig}_s|\text{PU}_s)$ is used to delete the subscription entry from the subscription table.

**Register Contract:** This is a multisig contract, which ensures that both parties have agreed upon the registered DSC. It maintains a DSC look-up table which comprises of the following fields: contract id, creator id, seller public key, buyer public key, DSC address, ABIs name. The register contract uses the functions discussed below to manage the look-up table.

- **contractCreate():** A newly deployed DSC can be added to the contract lookup table using
$Tx_{create}(DSC_{address}, DSC_{ABI}, ID_s, Sig_b, PU_b, Sig_a, PU_a)$ where $DSC_{address}$ and $DSC_{ABI}$ are the DSC address and ABIs respectively. $ID_s$ is the seller ID.

- $contractRemove()$: This ABI deletes the contract entry from the lookup table. It subsequently performs the $SelfDestruct$ operation resulting in removal of the storage and code from the state $[28]$. It is invoked by $Tx_{remove}(CID, Sig_b, PU_b, Sig_a, PU_a)$ where $CID$ is the contract ID.

- $contractGet()$: $Tx_{get}(CID, Sig, PU)$ issued by either of the parties to get the DSC contract address and the associated ABIs.

**Pricing Contract**: A pricing contract maintains a ledger with the following fields: timestamp, data type identifier, price, quality score and privacy risk score. Whenever a new DSC is deployed or a new subscription is added, the corresponding contract issues a message $M_{x\text{price}}(ID\text{type}, Hash\text{data}, Sig\text{contract})$ to record the price of the data type. $ID\text{type}$ is the data type identifier, $Hash\text{data}$ is the hash of the price details and $Sig\text{contract}$ is the signature of the issuing contract.

We have adopted a competition-based pricing model in our framework. This pricing strategy is suitable for highly competitive markets, such as ours, which have huge individual sellers base interested in selling their IoT data in return for incentives. In a competition-based pricing model, the seller can follow the market going rate charged by other individuals in a competition-based pricing model, the seller can follow the market going rate charged by other individuals selling the same data type. This strategy does not require any complex computation and dynamically varies based on the market trend. The competitor’s price information $Price_{d,t}^i$ recorded in the ledger for $i^{th}$ transaction is used to calculate the price index $P_{d,t}^i$ of data type $d$ at a certain time $t$ using Eq. [1]. Then, base price $Price_{d,base}^t$ is calculated by averaging $P_{d,t}^i$ for the number of transactions $S$ in a given time interval $T$ using Eq. [2]

\[
P_{d,t}^i = \frac{Price_{d,t}^i}{QS_{d,t}^i + RS_{d,t}^i} + 1
\]

\[
Price_{d,base}^t = \frac{\sum_{i=1}^{S} P_{d,t}^i}{S}, t \in T
\]

However, in a highly competitive scenario, price is not a major differentiating factor to draw the buyers. Therefore, the seller must provide value-added features. These value-added features could be the data satisfying high-quality demand of buyers or possess a high risk of privacy violation. We quantify these value-added features by the Quality score ($QS$) and privacy risk score ($RS$). Quality Score is the weighted average of the buyer’s demand for quality levels and preferences. The privacy risk score of data is calculated using the risk matrix technique proposed in [23]. The price of the data is proportional to the scores mentioned above. In addition to this, smart contract related execution fees ($P_{exe}$) can also be divided between the seller and buyer as per the negotiated terms. Our pricing model evaluates the price of a particular data type $d$ using Eq. [3] where $\beta$ is the agreed-upon share of $P_{exe}$.

\[
Price = (1 + QS + RS)P_{\text{base}} + \beta P_{\text{exe}}
\]

**Rating contract** - In the marketplace, actors should be trustworthy as economic interests are relevant. Reputation plays a crucial role in C2C (consumer to consumer) trading to build trust, facilitate a smooth transaction and reduce risk [33]. The rating contract calculates the reputation score based on the actor’s trading history in the marketplace.

Post-settlement, DSC issues a message $M_{x\text{rate}} = [T_{\text{value}}, F_i, F_j, Sig_{\text{contract}}]$ to rating contract to update the trade history between actor $i$ and actor $j$. Feedback $F_j$ is received by actor $j$, feedback $F_i$ is received by actor $i$ and $T_{\text{value}}$ is the transaction value of the current trade. The rating contract records following fields in the ledger: maximum transaction value in the trade history ($v_m$), total positive feedback received ($F_j^+$), total feedback received, total number of failed contracts $c_{\text{fail}}$ due to agreement violation, time of last request ($ToLR$) and the total number of transactions $T_{i,j}$ between actor $i$ and actor $j$ in a very short span of time from $ToLR$.

Rating contract evaluates the reputation score $RS_j$ of an actor $j$ by updating his previous reputation score $RS_j'$ based on the current feedback $F_j$ and tuning factor $\alpha$ using Eq. [4]. $RS_j$ is the reputation score of actor $i$. The exponential factor is the aging factor of the impact of contract violation. $\alpha$ is calculated using Eq. [5] where $FC$ is the feedback credibility (Eq. [6]), $TV$ is the transaction value (Eq. [7]) and $CA$ is the collusive activity (Eq. [8]). $\alpha$ is a positive integer and used to contrast possible collusive actor behaviors.

\[
RS_j = ((1 - \alpha)RS_j' + \alpha F_j)e^{-c_{\text{fail}}} \\
\alpha = (FC + TV)CA
\]

\[
FC = \frac{R_i}{R_i + R_j} \left( \frac{F^+}{F^- + F^+} \right)
\]

\[
TV = \frac{T_{\text{value}}}{v_m}
\]

\[
CA = \left( \frac{1}{T_{i,j}} \right)^a
\]

$\alpha$ tunes the latest received feedback based on the trading history of the actors and helps in mitigating malicious activity by a dishonest actor in the marketplace as explained below.

- A dishonest actor with a low reputation score may malign other actor’s reputation score by giving negative feedback. $FC$ ensures that the feedback credibility of such an actor is low.
- An actor can exploit its high reputation score by giving false negative feedback to other actors. $FC$ mitigates this activity by increasing feedback credibility based on the number of positive feedback ratings given by the actor.
- An actor may build up a good reputation by properly executing several low-value transactions, and then misbehave in a very high-value interaction. $TV$ prevents this by modulating feedback proportional to the transaction
value, i.e., for a low-valued transaction, the feedback increases the reputation score slightly, but the increase is considerable for a high-valued transaction.

- Two actors may collude with one another to increase each other’s reputation score. With an increasing number of transactions between two actors, CA tends to zero. Consequently, feedback loses its relevance.

The above evaluation of the reputation score is suitable for successful transactions only. We also consider the case when the agreement is violated and not fulfilled. Agreement violation should reduce the actor’s reputation score drastically, hence discouraging the actor from performing any such violations. To this end, we define violation factor \( VF \) that solely depends on the actor’s ability to fulfill the signed contract completely. It holds maximum weight in the calculation of the actor’s reputation score as given in Eq. 9 where \( (C_{\text{fail}}) \) and \( (C_{\text{total}}) \) are the number of failed and total contracts, respectively. The reputation score is calculated using Eq. 10 as \( \alpha \) and \( F_j \) are 0 during agreement violation.

\[
VF = 2 - 2^{\frac{C_{\text{fail}}}{C_{\text{total}}}} \tag{9}
\]

\[
RS_j = RS_j'VF \tag{10}
\]

V. ECONOMIC ASPECTS: EDSA MECHANISM

As stated earlier in Section III, the demands selection involves two steps. In the first step, the facilitator performs the matching and selection based on the buyer’s contextual requirements. The second step of selection is done based on the quantitative requirements at the seller end. The demand selection component of the off-chain layer uses an optimization model to allocate devices of the seller to a selected subset of the demands so that the sellers revenue is maximized. The selection and allocation of demands should meet the quality requirements of the selected buyers and also ensure that the battery capacity of the devices is sufficient to fulfill the assigned demands completely without any interruptions. This mechanism of energy-aware demand selection and allocation is defined as EDSA.

In this section, we formally state the EDSA problem. Given a set of demands where each demand is expressed in terms of data type, sampling interval, duration and quality, the question is to find a subset of demands that maximizes the revenue of the seller while satisfying the battery, quality and allocation constraints. Fig. 4 describes a sample demand selection and allocation scenario for a seller with three devices offering three different data types and four buyers with different data allocation scenario for a seller with three devices offering constraints. Fig. 4 describes a sample demand selection and allocation scenario for a seller with three devices offering constraints.

The following ILP formulation outputs a selection of demands that optimally maximizes the total revenue while meeting the battery, quality and allocation constraints. The objective function is the total revenue generated by the demands that are selected and allocated to an IoT device of the seller. The EDSA problem can be formulated as:

maximize \[ \sum_{i} \sum_{j} \sum_{k} x_{ij}^{k} Q_{ij}^{k} P_{ij}(q^{k}) \]

subject to

\[
\sum_{j} x_{ij}^{k} E_{ij}^{k} \leq B_i, \quad \forall i \tag{11}
\]

\[
\sum_{i} x_{ij}^{k} \leq 1, \quad \forall k, \forall j \tag{12}
\]

\[
x_{ij}^{k} q^{k} \leq Q_{ij}, \quad \forall i, \forall j, \forall k \tag{13}
\]

where the decision variables \( x_{ij}^{k} = 1 \) if data type \( j \) demand of \( i \) is assigned to \( j \), and \( x_{ij}^{k} = 0 \) otherwise. Eq. 11 captures the battery constraint of the devices. The allocation constraint in Eq. 12 ensures that each buyer demand is served by at most one device of the seller. Eq. 13 represents the quality constraint of the devices which defines the assignment restrictions.
Decision making in the demand selection and allocation can be regarded as the MKAR [29]. For each seller’s device (knapsack) a parameter of battery capacity is associated. Each buyer’s demand (item) has parameters of price (value) and power consumption (weight). Also, for each demand, a subset of sellers’ devices which satisfies the quality constraint of the buyer’s quality demand can be selected (assignment restrictions). The task of the EDSA is to determine the optimal demand selection and allocation to devices that maximizes the seller’s revenue considering the parameters and the assignment constraints.

MKAR have been addressed in the literature. [29] considered MKAR in steel industry application in which the profit and weight of each item is the same. A more generic problem, in which profits and weights are different, was studied by [30], in the context of wireless telecommunication. It uses Linear relaxation to find optimal vertex solutions followed by solving an instance of reduced MKAR problem iteratively. MKAR is NP-hard in strong sense and no simple method to run on resource-constrained devices such as dynamic programming is known to be applicable to the MKAR. Also, given the low latency demand of a marketplace, computing optimal solution may not be ideal in this scenario. We therefore use a greedy heuristic approach similar to [31] to solve the EDSA.

The intuition behind our algorithm is that selecting demands with high prices and low energy consumption may result in a high total revenue for the seller under energy constraints. Based on this intuition, we define the Normalized Revenue (NR) of a demand as the ratio of the generated revenue to the energy consumption of the demand. Our NR-based algorithm starts by initializing the list of demands (Line 1) and calculating the NR values for each demand in the list (Line 2-4). Then, the list of demands is sorted in descending order of NR values (Line 5-9). Note that, demands with equal NR values are further sorted based on their prices. The rest of the algorithm assigns demands to devices using the sorted demands list (starting from the demand with the highest NR value) checking the battery availability and device quality constraints and updates the available battery of the devices (Line 11-19).

**Algorithm :** NR-based algorithm executed by the seller

```
1: Initialization of the Demand list.
2: for each dem in Demand
3:     Calculate NR
4: end for
5: Sort demands in descending order of NR
6:     if elements in NR are equal:
7:         Sort demands in descending order of prices
8:     end if
9: end sort
10: Sort devices in ascending order of batter availability
11: for each dem in Demand
12:     for each dv in device
13:         Compare Device battery ≥ demanded energy
14:     end for
15:     Assign dem to dv
16:     Update the available battery of dv
17:     break
18: end for
19: end for
```

VI. IMPLEMENTATION AND EVALUATION

In this section, firstly, we provide a proof-of-concept implementation of the smart contracts, discussed in section IV, using the Solidity version 0.5.12. Then various scenarios and conditions with a single buyer and seller were thoroughly tested on private Ethereum blockchain Ganache. This is to ensure that the logical flow and execution outcome from the interactions of different smart contracts are as expected. Then we analyzed the cost of trade on an Ethereum public testnet. Secondly, we implemented the NR-based algorithm, presented in section V, in MATLAB to solve the EDSA problem. Evaluation based on simulation results provide insight into the seller’s revenue generation for different scenarios.

A. Proof of concept implementation

The Proof of concept implementation of the smart contracts was done on the Ropsten testnet network which resembles a public Ethereum network and behaves similarly to a production blockchain. It runs a proof-of-work blockchain and is used for testing purposes before deploying an application on the main network. Our smart contract[s] were implemented and deployed using Remix IDE[1].

It is worth noting that, in the Ethereum blockchain, any operation or transaction that modifies the blockchain or changes its state incurs fees, which need to be paid by the involved parties. These costs are estimated using the amount of gas consumed and the unit gas price. The gas consumed during any operation reflects the computational complexity or size of the smart contracts, while the gas prices are determined by the miners in the system. We used 10 Gwei gas price to evaluate the cost of different operations during data trading (the recommended gas prices can be found at [32]). Table II shows the costs of DSC contract deployment and the various transactions to achieve end-to-end data trading, where the total cost of all the operations sums up be USD 2.67555.

It can be observed that $T_{x_{add}}$ and $T_{x_{settle}}$ consumed more gas than other transactions. This is because these transactions involve write operations on the blockchain. $T_{x_{add}}$ require interaction with the pricing contract to fetch the price of the subscription and also update the pricing information in the ledger while $T_{x_{settle}}$ interacts with the rating contract to calculate and update the reputation score based on the latest feedback. It can be observed that deploying a new contract is expensive. Thus, a deployed trade contract could be reused if it provides a satisfactory trading experience for the users.

1Smart contract codes available at https://github.com/pooja239/DataMart
2http://remix.ethereum.org/
### TABLE II
**Cost of Operations in Ether and USD.**

| Operations    | Gas used | Cost Ethers | Cost (USD) |
|---------------|----------|-------------|------------|
| DSC deployment| 1212806  | 0.0121281   | 1.4675     |
| $T_{create}$ | 86458    | 0.0008646   | 0.10462    |
| $T_{add}$    | 265792   | 0.0026579   | 0.32161    |
| $T_{start}$  | 43581    | 0.0004358   | 0.05273    |
| $T_{settle}$ | 579676   | 0.0057968   | 0.70141    |
| $T_{delete}$ | 22883    | 0.0002288   | 0.02768    |

### B. Evaluation

In this section, we use our NR-based algorithm to solve the EDSA problem. The values of the parameters used in the simulations are given in Table III unless stated otherwise. The performance results are generated by averaging results of each simulation over 1000 iterations.

Fig. 5 shows the effect of increasing the number of demands requested for 10 data types by 50 buyers. Increasing the number of demands requested increases the demands served by the seller and the total revenue until the seller is not able to serve any more demands due to battery constraints. The left y-axis represents the total revenue generated while the right y-axis represents number of demands served and the residual battery percentage. We can see that increasing the number of demands requested from 10 to 500 causes a logarithmic growth for the revenue, which reaches saturation at a certain demand level (280-300) due to the limited batteries of the devices. This can be observed from the residual battery levels plotted in Fig. 5. Note that, the quality requirements of buyers may also limit the number of demands served by the seller, as some demands may have higher quality requirements than the quality of data provided by the seller.

Next, Fig. 6 demonstrates the effect of increasing the battery capacity on the total revenue of a seller with a single device. We observe that the revenue increases linearly with the increasing battery capacity from 500mAh to 3000mAh. As the battery capacity increases, the seller can select and serve more demands and generates a higher revenue. The residual battery does not change much, however, the percentage of the residual battery decreases, resulting in better utility of the battery capacity. It is observed that with the linear increment of battery capacity, total revenue generated is increasing linearly.

Finally, we analyze the effect of decreasing the number of devices and increasing battery capacity per device while keeping the overall battery capacity constant on the total revenue and residual battery in Fig. 7. The main aim of simulating this scenario is to analyze the impact of increasing the number of devices owned by seller on the generated revenue. The overall battery capacity with a seller is kept fixed to capture the original trend of increasing number of devices rather than increasing battery which will linearly increase the generated revenue. As we move from 10 devices with 300mAh batteries to 1 device with 3000mAh battery, the total revenue increases. This could be explained by the smaller battery capacities and residual batteries remaining on the devices. Devices with small batteries cannot serve demands that require high energy consumption. Furthermore, the residual batteries remaining on the devices cannot be combined and utilized to serve more demands. Thus, dividing the total battery capacity between multiple devices results in lower total revenues and higher unutilized residual batteries. It is preferable for the seller to invest on single IoT device with better battery capacity rather than on multiple IoT device with smaller battery capacity.

### VII. Conclusion

In this work we presented a multi-layered blockchain based framework, which considers both computing and economic aspects of trading sensing data in real-time from resource-constrained IoT devices. We leveraged smart contracts for managing the agreement life cycle that enables automatic...
transaction workflow to provide efficient trading of data without any intermediaries. We present the proof-of-concept implementation of the smart contracts. To improve the sustainability and usability of the marketplace, we also formulated the EDSA problem based on MKAR, which selects and allocate demands to maximize the seller’s revenue. If the prices are chosen according to the costs, this scheme also maximizes the total profit for the seller. We adopted a greedy approach using normalized revenue to solve the EDSA. We also simulated various scenarios to analyse the impact of the requested demands on the battery drainage of the seller’s devices. In our future work, we will consider maximizing the number of demands selected as an additional optimization objective and use a multi-objective optimization framework for demand selection and allocation problem. We will also analyze the performance of the proposed real-time IoT data marketplace and the NR-based algorithm experimentally using IoT hardware.

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