Validation and Verification of Data Marketplaces

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Abstract. This paper presents a Validation and Verification (V&V) model of Data Marketplaces. Data is extracted from the sensors embedded within the Smart city, infrastructure, or building via Application Programming Interfaces (APIs) and inserted into a Data Marketplace. The technology is based on smart contracts deployed on a private ethereum blockchain. Current issues with data in Smart cities, infrastructure, buildings, or any real estate, are the difficulty of its access and retrieval, therefore integration; its quality in terms of meaningful information; its large quantity with a reduced coverage in terms of systems and finally its authenticity, as data can be manipulated for economic advantage. In order to address these issues, this paper proposes a Data Marketplace model with a hierarchical process for data validation and verification where each stage adds a layer of data abstraction, value-added services and authenticity based on Artificial Intelligence. By using a blockchain, this presented approach is based on a decentralised method where each party stores the data. The proposed model is validated in a real application with live data: Newcastle urban observatory smart city project.

Keywords: Data Marketplace, Smart Cities, Smart Buildings, Real Estate, Blockchain, Smart Contracts, Artificial Intelligence.

1 Introduction

Smart cities, infrastructure, buildings and any real estate, as the natural outcome of a construction project, face digital challenges due to the nature of the physical environment of the design and built industry. In order to deliver a construction project or a product such as a building or an airport, the required framework comprises a large number of stakeholders (investors, insurers, designers, regulators) and a lengthy process divided into stages (planning permission, feasibility, concept and detailed design, construction, commissioning). The intrinsic properties of this particular ecosystem create fundamental digital issues: a) There is no clear data ownership or responsibility that covers the entire life cycle of the digital project from creation to decommissioning. Several independent organisations that seek economic profits may be involved in different stages with competing interests. In addition, companies organically evolve, change ownership, or even face liquidation. b) The final users are left with a product to manage, commercialise, or maintain without input on the digital design or data documentation. Normally, digital system upgrades and enhancements require re-starting again due to incompatibility issues. c) Due to this fragmented process, there is no efficient digital lesson learnt from the delivered projects that support the optimisation of their future integration within the design and build construction methods. Current digital platforms available such as Building Information Modelling (BIM) and Digital Twin still lack a clear delimitation of ownership, responsibility and maintenance.

In addition, Smart cities, and any Real Estate in general, also face four main key data issues: a) Difficulty to access real time-data automatically. Data can be stored within siloed servers or inconsistent nomenclature or structure. b) The quality of the data extracted is not normally very valuable with low statistical relevance due to its fragmentation where manual human intervention needs to fill the gaps or extrapolate it in order to obtain meaningful information. c) Large quantity of data with reduced coverage in terms of systems detriments the required complexity of data models for Bussiness Intelligence. d) Data users can not be guaranteed data is authentic. Cybersecurity attacks can manipulate stored data at the edge to make it look genuine. Data can be artificially manipulated to obtain an economic reward, such as an insurance premium.

1.1 Research proposal

This paper proposes a Validation and Verification (V&V) model of a Data Marketplace based on Artificial Intelligence that manages live data streams from smart building or city systems addressing both digital and data issues. The presented model applies a hierarchical process for data verification and data validation where each layer provides a layer of data abstraction, value-added services and authenticity via Artificial Intelligence algorithms. The main three applications of AI are used in the V&V model: classification, clustering and prediction. The practical application of the proposed Data Marketplace consists of three layers of verifications:

- **Bronze verification:** selects, retrieves and classifies data inserting it into the smart contract based on a private ethereum blockchain;
- **Silver verification:** analyses and clusters the data and reports any values that do not meet a predefined threshold, range or rule as a value-added service. The silver validation has value for insurers or property managers;
- **Gold verification:** makes data prediction. The gold validation has value for city or asset managers and city or property developers.

The proposed V&V model is based on a private ethereum blockchain solution that provides a secure and decentralised approach where each party or stakeholder owns a copy of the distributed ledger removing the need for a central assessor.

1.2 Research structure

The V&V model of data marketplaces has been applied to a real application with live data: the University of Newcastle smart city project. Data is extracted via Application Programming Interfaces (APIs) and stored in a private ethereum blockchain at University College London (UCL). Section 2 provides the research background of data marketplaces. Section 3 defines the V&V model of the proposed Data Marketplace whereas Section 4 describes its practical implementation. Finally, conclusions are shared in Section 5.

2 Research Background

2.1 Models and Algorithms

A blockchain enabled data marketplace solution is modelled as a weighted directed graph where each edge represents the transactional flow of data and each vertice represent the different sellers and buyers [1]. Distributed Big Data platforms implement a digital data marketplace based on the blockchain mechanism for data transaction integrity [2]. Data marketplaces support data providers and data requesters to retrieve the value of the data by means of combination, reconstruction, or reinterpretation through the exchange of shared data profiles [3]. An interactive platform facilitates the interactions between data providers and users where data is shared only after the match between the description items of data requests [4]. A distributed online marketplace uses an Ethereum framework to engage buyers and sellers in e-commerce transactions without the need for a central management entity [5]. Data values are efficiently guaranteed by the best possible value assigned to each data item based on the placement of data in the network, storage and processing power [6]. A real-time matching mechanism efficiently buys and sells training data for Machine Learning (ML) tasks based on prediction tasks and accuracy [7]. Open data providers and users within similar knowledge sharing activities are interconnected to increase the knowledge transfer within the ecosystem [8]. A 2D spatial data marketplace defines a data model based on a logical representation as a quadtree [9].

2.2 Economic Model

A criteria for interactive pricing in a data marketplace is based on three concepts: non-disclosure, arbitrage-free and regret-free [10]. ProDataMarket is a platform that shares and monetizes linked geospatial data based on property assets [11]. A model-based pricing framework prices ML model instances instead of pricing the data itself [12]. A transparent monetization system based on an ethereum Distributed Ledger Technology (DLT) and solidity smart contracts trades off between the overhead of tracking Internet of Things (IoT) data on a blockchain versus the accuracy of the monetization for data [13]. A broker assigns value to data owners according to their contribution to incentivize data sharing [14].

2.3 Smart Cities

Data Marketplace for smart cities can be served as several models based on the ownership and operation of the data source where sharing incentives shall not lead to concentration of monopolies that can manipulate its value [15]. IOTA technology is a blockchain developed for IoT networks that supports peer-to-peer transactions without centralised authorities collects information from different sensors in Smart cities via APIs [16].

2.4 Internet of Things

An architecture for a dynamic decentralized marketplace for the trading of IoT data is based on trust-less brokers that match and select potential data providers based on the consumer's requirements [17]. IoT data streams are traded and exchange in pairs of data providers and consumers without any prior assumption of mutual trust [18]. IoT device vendors and AI/ML solution providers interact, collaborate and create actionable insights in a blockchain-based, decentralized and trustless data marketplace that will lead to a variety of services [19]. A review system confirms the reputation of a data owner or the data traded before a transaction occurs [20]. The Intelligent IoT Integrator (I3) is a real-time data marketplace architecture platform that enables the possibility of data brokers to buy "raw" data, apply data analytics and sell back refined data streams [21]. The model uses Message Queuing Telemetry Transport (MQTT) publish-subscribe brokers integrated with an authentication and access control module [22]. An algorithm responds to data consumer's queries balancing the buyer's budget constraints and the seller's compensation for the provided IoT data services [23].

2.5 Semantics

A data marketplace based on a federation of eleven IoT deployments is applied to heterogeneous application domains to ensure the interoperability of data streams, based on the virtualisation of sensors in the cloud [24]. Meta-data and dynamic context data support the data preparation phase through a semantical approach [25]. Automatic handling of users' requests by means of Semantic Web technologies is based on a semantic model that describes the access policies [26].

2.6 Privacy and personal information

Sterling is a decentralised marketplace for private datasets that enables privacy-preserving distribution by using smart contracts run on a permissionless blockchain in trusted execution environments [27]. IoT generated personal data is commercialised protecting the privacy and data rights of data generators [28]. WibsonTree is a cryptographic primitive designed to preserve users' privacy by allowing them to demonstrate predicated on their personal attributes, without revealing their values [29]. A dynamic cloud-based marketplace of near real-time human sensing data is designed for environments where traditional Information Technology (IT) infrastructures are not well developed [30]. A scheme of a data marketplace in the healthcare industry negotiates data based on metadata and data properties rather than the raw data itself [31]. "Digital Me' uses an AI agent as an intermediary between buyers and sellers to anonymise personal data in accordance with the General Data Protection Regulation 2018 [32]. IoT generated personal data is traded based on a thorough analysis of personal data with a specific focus on the challenges and risks within a data licensing framework [33]. A neural network in Blockchain configuration encrypts personal information to validate the transmission channel [34].

3 Validation and Verification of Data Marketplace Model

The Data Marketplace model is defined as an M-dimensional universe of X data items where each individual entity or data within the universe is distinct from the others. We consider the universe from which the data marketplace is created as a relation U that consists of a set of X M-tuples, $U = \{v_1, v_2 \ldots v_X\}$, where $v_i = (l_{i1}, l_{i2} \ldots l_{iM})$ is data item i and l_{iM} are the M different data attribute values for i=1,2..X. The important concept in the development of this proposed V&V model is that data is defined as $D_t(n(t),v)$ where:

- n(t) is a variable N-dimension vector with $1<N<M$, n(t) is variable so that values can be added or removed based on the value-added services;
- t is the V&V stage represented as time t where $t>0$;
- v is the value of the data D_t at time t.

The Data Marketplace model is based on a hierarchical process where users validate and verify data in order to add quality in terms of authentication or value-added services. The process of Validation & Verification, VV_{NM}, is defined as:

- Horizontal layer users (1, ..., n, ... N) add validation to the data: this N process confirms the data stored in the smart contract is authentic;
- Vertical layer users (1, ..., m, ... M) add verification to the data: this M process includes a higher layer of abstraction based on Artificial Intelligence for data analytics that provides value-added services.

Data value *v* of $D_t(n(t),v)$ at time or stage *t* is defined as:

$$v=\sum_{m=1}^{M} m^2 * \sum_{n=1}^{N} n$$

Each horizontal *n* layer acts as a data checker that confirms the inserted data into the marketplace whereas each vertical layer *m* acts as a data transfer that filters, aggregates and refines the data to meet different clients and customers' information needs based on Artificial Intelligence. In a nutshell, the more horizontal N the more genuine the data is and the more vertical M, the more valuable (Fig. 1). As a practical scenario, this paper proposes a Bronze, Silver and Gold verification service approach.

3.1 Bronze verification

Bronze verification confirms data is real and authentic inserting it into the private ethereum blockchain via a smart contract. The purpose of this layer is to use data as a general information source such as ranking for visualisation or dashboards. Artificial Intelligence based on classification algorithms that include naive Bayes, decision trees, random forests, support vector machines, k nearest neighbours divide the input variable into different classes and then predict the class for a given input using supervised learning.

3.2 Silver verification

Silver verification inserts a layer of value-added services analysing the value of the data. The silver validation is used for auditing purposes such as insurance, facilities management to confirm if the smart city system or asset is compliant with law or regulation such as fire alarm system monitoring within a smart building. The silver validation assembles any smart city Key Performance Indicator (KPI) as a benchmark between different smart cities. Artificial Intelligence based on clustering algorithms that include k-means, fuzzy, or hierarchical divide and organize data points into groups based on similarities within members of the group with unsupervised learning.

3.3 Gold verification

Gold verification purpose is for Big Data models that analyse several data sources and predict future values. This layer would be used by asset managers or property developers. Artificial Intelligence and Machine Learning based on regression algorithms that include linear regression, lasso regression, logistic regression, multivariate regression, multiple regression predict the output values based on input data points via supervised machine learning algorithms.

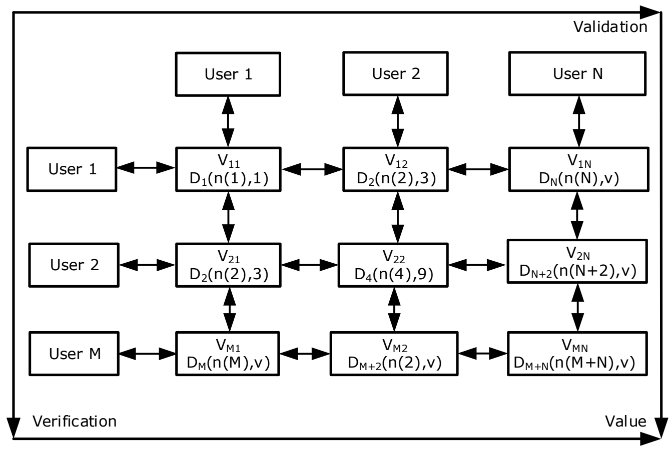

Fig. 1. Data Marketplace model

4 Experimental Results

The Data Marketplace model has been validated within Newcastle urban observatory smart city project [35] where data has been extracted by open protocol RESTful (Representational State Transfer) APIs based on a JavaScript Object Notation (JSON) data structure (Fig. 2). The blockchain is implemented via Go Ethereum (Geth) and the smart contract via Solidity. The IoT platform has been developed on Java Maven with the embedded Blockchain and smart contract managed by web3j library. The server is a dedicated computer specifically built for Linux and optimised for mining.

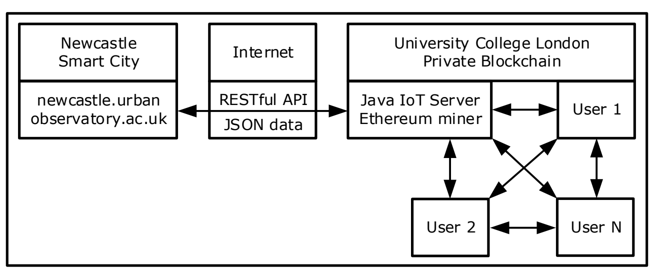

Fig. 2. Data Marketplace architecture

Each validation or verification process generates two smart contract transactions:

- Data Insertion (DI): generated by the algorithms that create value-added services
- Data Value (DV): represents the Validation & Verification value v

Note that the purpose of the experimental results is to confirm the proof of concept of the data marketplace model rather than the V&V of the data itself. İn addition, variables are considered independent although they are stored in the same Blockchain. Table 1 defines the variables used in the validation process for a month of data collection (November 2020).

Table 1. Data Variables parameters

Variable	Unit	Data Points	Average	Max Value	Min Value
Particular Matter 2.5	ugm -3	2974	4.37	20.32	0.19
Carbon Monoxide	ugm -3	1089	251.69	489.04	187.69
Sound	dB	37632	64.86	87	54
People Count	Person	4230	0.01	6	0
Car Count	Car	4230	0.39	7	0

Table 2 defines the blockchain addresses and gas price of the smart contract. Data inputs to the blockchain have been limited to 500 values due to software constraints.

Table 2. Smart contract parameters

Parameter	Value
Account Address	0xa35b5e29e84161c9aa75d519dd8f947f7e8e9eea
Contract Address	0x18b89d51cb0c30c07fbedf710ebb76fe87748e18
Gas Limit	22000000000
Gas Price	21000

4.1 Horizontal Validation

Different validation stages confirm that the data extracted from the different Smart City sensors is authentic. Table 3 shows the average values for the five data variables validation stages and smart contracts, Data Insertion (DI) and Data Value (DV), within the blockchain. Experimental results also include the respective transaction fees, gas price and mining time.

Table 3. Horizontal Validation – smart contract and blockchain values

Validation Stage	Data Input	Gas Price	Transaction Fee (GWEI)	Mining Time	V&V value v
Initialisation	N/A	2.58E+05	5.69E-03	1.09E-03	0
1-DI	500	1.49E+06	3.27E-02	1.79E-03	1
1-DV	1	4.20E+04	9.24E-04	7.68E-04	
2-DI	500	1.26E+05	2.78E-03	1.55E-03	2
2-DV	1	2.70E+04	5.94E-04	8.24E-04	
3-DI	500	1.93E+05	4.24E-03	2.31E-03	3
3-DV	1	2.70E+04	5.94E-04	7.42E-04	

The horizontal validation (Table 3) demonstrates the general blockchain equation Transaction Fee (GWEI)=Gas Limit x Gas Price where the Gas Limit is a constant value (2.20E+10). Data Insertion (DI) is more expensive to mine, from a transaction fee and mining time perspective, than Data Value (DV). This is due to

DI stores a larger amount of data within the block structure, an array of doubles, rather than the single integer stored by DV (Fig. 3). The transaction fees and mining times do not fully correlate linearly to the amount of data stored in the blockchain. The main reason is Go Ethereum consensus algorithm and the random nature of the mining process.

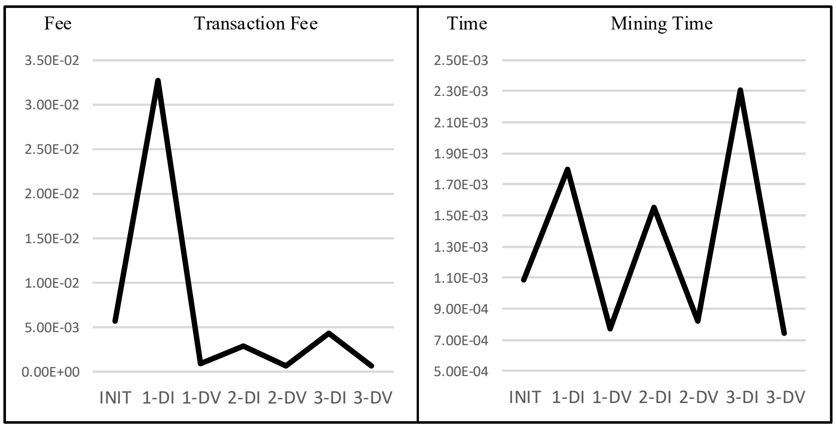

Fig. 3. Horizontal Validation

4.2 Vertical Verification

Different vertical verification stages value-added services to the data. The bronze verification introduces the extracted JSON data via the API into smart contracts, classifies and finally confirms its and authenticity. The silver verification clusters the values that are above average as a simple representation or rule of uncompliant values. The gold verification predicts the next uncompliant value. As the values from the silver verification are considered as a time series, the prediction algorithm is based on a Long Short Term Memory (LSTM) network. Table 4 shows the average values for the five data variables during the different verification stages within the blockchain that includes also transaction fees, gas price and mining time.

Table 4. Vertical Verification – smart contract and blockchain values

Validation Stage	Data Input	Gas Price	Transaction Fee (GWEI)	Mining Time	V&V value v
Initialisation	N/A	2.58E+05	5.69E-03	1.10E-03	0
1-DI	500	1.49E+06	3.28E-02	2.38E-03	1
1-DV	1	4.20E+04	9.24E-04	7.55E-04	
2-DI	173.4	2.01E+05	4.43E-03	2.26E-03	4
2-DV	1	2.70E+04	5.94E-04	8.03E-04	
3-DI	1	8.91E+04	1.96E-03	1.74E-03	9
3-DV	1	2.70E+04	5.94E-04	7.02E-04	

The vertical verification confirms the transaction fee (GWEI) equation with consistent results as previous the horizontal validation (Table 4).

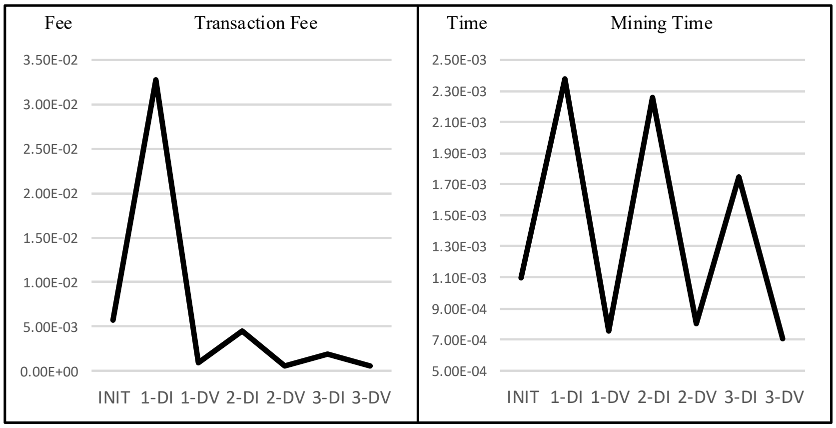

Fig. 4. Vertical Verification

The transaction fees and mining time are more dependent on the block structure rather than the relative amount of information stored within the blocks themselves (Fig. 4). As DI stores a larger amount of data within the block structure than DV, the transaction fees and mining time is greater.

4 Conclusions

This paper has presented a Validation and Verification model for a Data Marketplace based on Artificial Intelligence. The proposed method is based on a hierarchical process for data verification and data validation where each stage adds a layer of data abstraction, value-added services and authenticity via Artificial Intelligence algorithms. The defined approach has been validated in a real application with live data: University of Newcastle smart city project where data is obtained via real-time APIs. Experimental results demonstrate that a private Go Ethereum blockchain and Solidity smart contracts combined with AI successfully deliver the value-added services in a decentralised network. The private blockchain performs as expected with a linear relationship between transaction fees, gas limits and gas prices. Transaction fees and mining times are more dependent on the block structure rather than the amount of information contained within the blocks themselves. Future work will include additional verification and validation stages to confirm the presented conclusions where the V&V model will be expanded with further data variables and structures. Additional AI algorithms such as Natural Language Processing (NLP) will be applied to enhance the offered services in the Bronze, Silver and Gold approach.

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Appendix

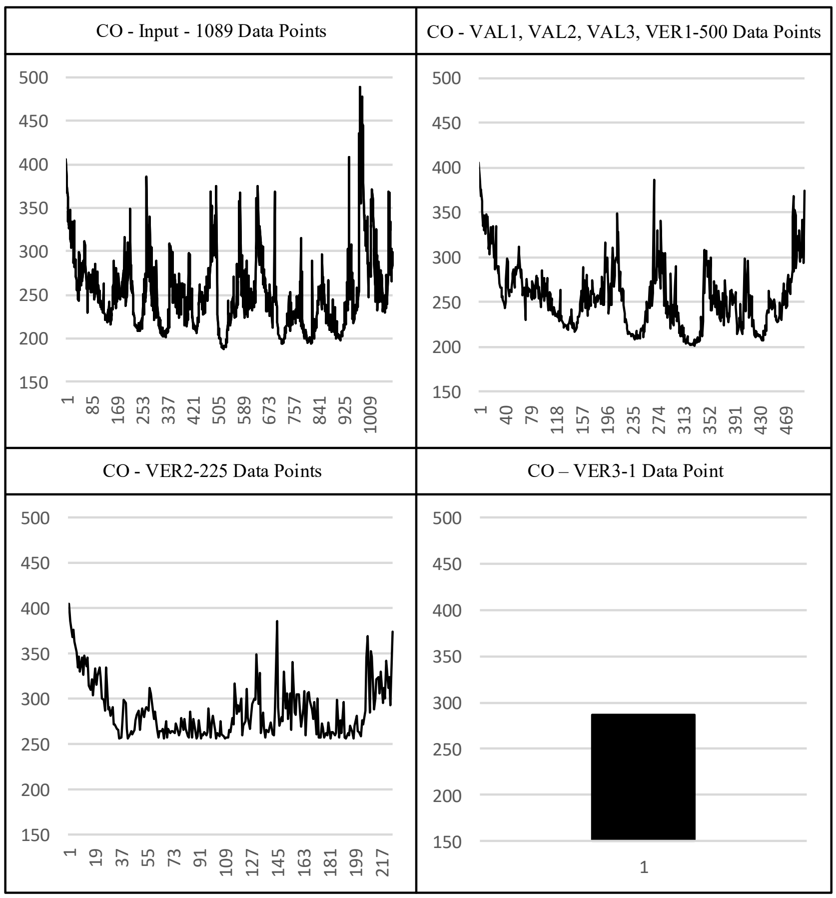

Fig. 5. Example Data Values (CO) in the Validation (VAL1, VAL2, VAL 3) and Verification (VER1, VER2, VER3) model