Time Estimation for a New Block Generation in Blockchain-Enabled Internet of Things

Malka N. Halgamuge, *Senior Member, IEEE,* Geetha K. Munasinghe, and Moshe Zukerman, *Life Fellow, IEEE*

***Abstract*— The Internet of Things (IoT) has emerged with Distributed Ledger Technology (DLT) to address existing scalability challenges and improve the trustworthiness of machine-to-machine communication. Among the numerous potential benefits of combining IoT and DLT, Blockchain, a subset of DLT, is a crucial enabler to accelerate secure IoT adoption. Appending a new block to a blockchain, especially in a blockchain-based IoT ecosystem, requires more delay than expected. This delay is one of several issues limiting the broader adoption of blockchain within the IoT domain. To assess this delay, we develop a new comprehensive model to estimate the time required to generate a new block in a blockchain-enabled IoT system. To this end, we develop sub-computation models and compare time consumption associated with the block generation process by conducting an extensive analysis of the following selected IoT layers: device layer, cluster head layer, fog/edge layer, and cloud layer. Our study identifies potential time-consuming steps in adding a new block to a network. Our results demonstrate that the type of blockchain framework and data encryption algorithms could affect the block generation time and that Avalanche, Conflux, Algorand, Polkadot Hyperledger Fabric outperforms *Ethereum* in terms of block generation time in IoT networks. On the other hand, the blockchain framework does not play a significant role in block generation time for smaller data packets. We also observed the benefit of using 256-bit *ECC (elliptic curve cryptography)* encryption and the fog layer in IoT networks to enhance the scalability of the block generation process. All in all, our results indicate that the total block generation time varies depending on the selected IoT framework, data encryption algorithm, blockchain type, and key functions of the layers. However, we found that time delays associated with queuing or block size are negligible relative to the other key components of block generation time.**

***Index Terms*—Blockchain, Distributed Ledger Technology (DLT), new block, Internet of Things (IoT), fog computing, cloud computing, encryption algorithm, computation time.**

I. Introduction

With the advanced technologies in the Internet era, people's lifestyles have been enhanced in different ways. The Internet of Things (IoT) is one of the key technologies facilitating smart life opportunities with daily substances connected to the Internet. Furthermore, it aids consumers in delivering customized solutions based on specific user requirements across multiple platforms. The main reason for IoT adoption is to derive intelligent information from the available data to make real-time decisions, analyze performance, and predict parameters. However, the full potential of the IoT has not been achieved yet due to factors such as security loopholes, lack of standards, heterogeneous behavior of devices, and varied communication protocols. As forecast by Holst 2021 [1], the number of connected devices (IoT) worldwide will almost triple from 8.74 billion in 2020 to more than 25.4 billion IoT devices in 2030. Correspondingly, scalability and the current centralized architecture in the IoT network to handle authentication, authorization, and device connections will be a bottleneck in the future world. Therefore, blockchain technology has been used to mitigate weaknesses in security [2], [3], privacy, scalability, and transaction transparency within the IoT framework.

A blockchain is a Distributed Ledger Technology (DLT) that allows storing a linked list of records as a chain with additional information for transactions. It is an alternative computer model with key strengths such as tracking and recording each transaction information and unmodifiable transaction records. Thus, blockchain technology provides a secure and cost-effective mechanism for transactions compared to traditional methods. Blockchains are available in different types, such as private (permissioned) and public (permission-less). *Bitcoin, Ethereum, Cardano, Avalanche, Conflux, Algorand,* and *Polkadot* are considered public blockchains, and *Hyperledger Fabric* is an example of a private blockchain. Depending on the application requirements, users have to adopt a suitable blockchain type. Estimation of the time for generating a new block is especially important because blockchains are computationally expensive and require significant bandwidth overhead and long latency. The PoW-based blockchain framework, in particular, requires a significant time duration to mine blocks. For example, a typical PoW, such as *Bitcoin*, takes 10 minutes to mine each block [4]. Estimation of the generation time of a new block can indicate whether or not a particular PoW is suitable to meet the Quality of Service (QoS) requirements of specific IoT applications.

Using blockchain technology in the IoT framework delivers several advantages [5], such as (i) the ability to track and analyze any activity of the chain for authorized officers, (ii) improvements of the overall security, and (iii) creating smart contracts to execute agreements if specific conditions are available. It is essential to make real-time decisions in the IoT

M. N. Halgamuge is with the Department of Information Systems and Business Analytics, RMIT University, Melbourne, VIC 3000, Australia e-mail: (malka.halgamuge@rmit.edu.au).

G. K. Munasinghe is with Sine Group Pty Ltd, Adelaide, SA 5000, Australia e-mail: (geetha.munasinghe@sine.co)

M. Zukerman is with the Department of Electrical Engineering, City University of Hong Kong, Hong Kong e-mail: (m.zu@cityu.edu.hk)

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by analyzing the data transmitted from millions of connected devices.

A. Motivation

In a blockchain, every transaction in a decentralized system must undergo several processes requiring substantial processing power and time [6]. Each data transaction must go through various processes, including acceptance, mining, dissemination, and validation by a network of nodes. A new block generation time is straightforward and independent of the delay in IoT layers (fog/edge/cloud) when IoT applications are not considered. In blockchain-enabled IoT systems, however, the delay on the various IoT layers directly impacts the block generation time, affecting the time required for data to be added to the blockchain.

To add IoT transactions to the blockchain, the block generation time across the whole IoT system should be less than the block interval (time) of the chosen blockchain framework. Generating a model to estimate the total block generation time will assist the professionals in discovering the areas that need to be considered to reduce the total response time. So far, however, there has been little discussion about the total computation time in the IoT framework. Even though some studies [7]–[9] have focused on generating models for time consumption in different areas in the sensor network and the IoT framework, a complete processing time estimation model for the entire framework has not been generated.

Therefore, our model analyzes all functions in each IoT layer and proposes a new, comprehensive, time estimation model for understanding the impact of Blockchain-Enabled IoT on the block generation process and evaluating the block generation time in the IoT environment (device layer, cluster head layer, fog/edge layer, and cloud layer). In addition, in our proposed model, transaction queuing time and blockchain network latency are taken into account.

Block time or block processing time is the required time duration to create a new block or the time it takes to mine a block or file in a blockchain. Block processing time is the actual time within a network to validate transactions for one block and add a new block to the blockchain. Based on the blockchain type, the different blockchain frameworks require different time durations. For example, the estimated block time in Bitcoin is 10 minutes, whereas Ethereum's is between 10 and 19 seconds.

The effectiveness of encryption algorithms outside the scope of blockchain applications has been extensively explored, e.g., [10]–[12], as encryption helps protect information and sensitive data and can improve the security of communication between client apps and servers. For blockchain applications, the encryption time will account for a significant portion of the total time spent on the block creation process. No existing work provided an evaluation of the time to estimate generating a new block in a blockchain-enabled IoT network. In this study, we explore and analyze encryption methods that are crucial when selecting a blockchain framework.

B. Main Contributions of this Paper

The main contributions of this paper include the following.

- We develop a new comprehensive time-computation model of appending a new block to a blockchain to estimate the new block generation time in a blockchain-based IoT ecosystem. This requires the development of sub-time computation models for each IoT layer (device layer, CH layer, fog/edge layer, and cloud layer).
- We identify each IoT layer's extreme time consumption scenarios where we simulate our new time computation model under different circumstances (varying data packet size, blockchain type, and encryption algorithm).
- Using the model, we also identify the significance of the fog layer for the block validation process by which we achieve improvement of the efficiency of the entire block generation process.
- We discover using our proposed model that the existing *Hyperledger Fabric, Ethereum, Avalanche, Conflux, Algorand, Polkadot* blockchain frameworks, and 256-bit ECC (elliptic curve cryptography) encryption algorithm enhances the performance and scalability of the block generation process in the blockchain-enabled IoT platform.
- We observe based on our new model that the blockchain framework does not play a significant role in block generation time for smaller data packets.

C. Structure of Paper

The remainder of the paper is organized as follows. Section II explains the background and related work. Section III highlights key layers of the IoT architecture, their main functions, and the total computation time required to generate a new block in the blockchain-based IoT architecture. Section IV presents the simulation setup, Section V demonstrates results and discussion in Section VI. Section VIII concludes the paper and outlines possible future improvements (Section VII) for the IoT and the blockchain technology.

II. Background and Related Work

Most blockchain implementations that integrate into IoT systems, such as *Ethereum* (Geth or Parity implementations) and *Hyperledger Fabric*, generate blocks regardless of whether sensing data arrives at the blockchain network. This block time is generally stable and primarily determined by the hardware infrastructure and a blockchain network's consensus protocol configurations. For instance, the PoW consensus protocol of Ethereum has a mechanism to auto-adjust the mining difficulty to ensure that the block time is stable around the desired figure, regardless of the total hash rate of the network.

Previous literature has noted the importance of improving the scalability of the IoT framework without slowing down the transaction processing speed. Different studies have been conducted to improve the efficiency of the data processing in the IoT layers using different mechanisms, such as (i) introducing energy optimization techniques [9], [17], [18], different network architectures [10], [19], [20] for sensor network, (ii) integrating edge and fog layers into the IoT framework with enhancements [8], [21]–[24], (iii) introducing various validation processes for the blockchain [25], and (iv)

TABLE I
SUMMARY OF BACKGROUND LITERATURE

Study	Research Focused Area	Blockchain Type	Sensors / Devices	Cloud / Shared Network	Fog/Edge	Security Mechanism	Purpose of the Research	Time Considerations
Mondal *et al.* (2019) [10]	IoT architecture	*Bitcoin*	Yes	Yes	No	Data encryption, traffic encryption using SSL / TSL protocol, authentication	Proposing a tamper-proof block validation process	Single block validation time
Jang *et al.* (2019) [6]	IoT architecture	*Hyperledger Fabric*	Yes	Yes	Yes	Not mentioned	Develop block chain based fog system architecture	Total response time (adding new block)
Tuli *et al.* (2019) [11]	Fog / Edge and cloud layers	Not mentioned	Yes	Yes	Yes	Integrity, authentication, encryption	Facilitating a framework for end-to-end IoT-fog (edge)-cloud by reducing service delivery latency	Service delivery latency to fog/cloud layer (network propagation delay and application execution time)
Damianou *et al.* (2019) [13]	Edge layer and the blockchain enabled IoT	Novel and innovative hybrid blockchain	Yes	Yes	Yes	Default security in the blockchain & Edge network	To increase overall performance by decreasing the memory capacity	Cloud service response time
Zhou *et al.* (2018) [12]	Blockchain security, data storage, and homomorphic computation	*Ethereum*	Yes	Yes	No	*ECIES* encryption, *ECDSA* digital signature	Ensure data security of the blockchain-based IoT network using homomorphic computation without accessing information	Cryptographic and mathematical computation processing time block processing time
Liang *et al.* (2017) [14]	IoT (drone data collection)	*Bitcoin*	Yes	Yes	No	PK cryptography	Develop a model to secure drone data using the blockchain technology	Average response time against data size and the number of drones
Lei *et al.* (2017) [15]	Vehicular network / Intelligent transport system (ITS)	*Bitcoin*	Yes	Yes	No	Blockchain-based key management scheme	Security key management for Intelligence transportation system	Processing time of the cryptographic algorithm
Gervais *et al.* (2016) [16]	Cloud, proof of work of the blockchain technology	*Bitcoin, Dogecoin, Litecoin, Ethereum*	No	Yes	No	Default security	Analyze security and performance of the blockchain consensus process based on network propagation, different block sizes, block generation intervals,	Block generation time
Halgamuge *et al.* (2009) [9]	Sensor network energy consumption	No	Yes	No	No	Not mentioned	Propose a comprehensive energy model for sensor network	Sensor transition time (sleep to idle, idle to sleep), Active time, sleep time, sensing time, sensor reading and writing time
Our Model	**Blockchain enabled IoT**	**(*Ethereum, Hyperledger Fabric, Algorand, Conflux, Polkadot, Avalanche*)**	**Yes**	**Yes**	**Yes**	**Authorization, access control, encryption, integrity**	**Estimate the computation time required to generate a new block in a blockchain-enabled IoT system**	**Individual functional time in each IoT layer (Sensor, CH, Fog, Cloud), block propagation time (*Ethereum, Hyperledger Fabric, Algorand, Conflux, Polkadot, Avalanche*), cryptographic processing time in each layer**

DLT-based IoT data trading over the narrowband Internet-of-Things system [26], [27]. Table I shows a summary of some of the prior studies that used blockchain-based IoT networks. However, in reviewing the prior studies, not much evidence was found to assess the importance of the time consumption of each significant function when processing a block in the IoT.

Another significant aspect is the overall delay in the block generation process due to different factors. Numerous studies have attempted to explain why the slowness of generating blocks such as network delay, consensus process in the blockchain, service delivery delay, response time, limited capabilities of the IoT devices, and data processing time within the different IoT layers. Damianou *et al.* [13] use novel and innovative hybrid blockchain architecture to increase the overall performance of block generation time by decreasing the memory capacity. Lei *et al.* [15] consider the cryptographic processing time of the intelligent transportation system (ITS) and propose a security key management module to improve block generation by enhancing the security of the process.

Moreover, a strong relationship between block generation time and the blockchain type has been reported in the literature. Table VII and Table VIII (Appendix) show a comprehensive comparison of different features of blockchain frameworks to determine the most efficient blockchain type. The comparison between, for example, block interval, median block propagation time, block mining time, and cross-chain interoperability of the different blockchain types: *Bitcoin, Litecoin, Ethereum, Hyperledger Fabric, NEO, Cardano, EOS, Algorand, Conflux, Binance (BNB), Polkadot (DOT)*, and *Avalanche* are presented. Several models have used *Bitcoin* and *Ethereum* for their studies. However, when considering the block interval time and processing time, the advantage of using those types for real-time decision-making systems is arguable.

Jang *et al.* [6], Zhou *et al.* [12], and Liang *et al.* [14] simulate sample modules to generate a block using the IoT architecture. However, the cluster head (CH) layer has not been taken into consideration in all models. In the model, developed by Liang *et al.* [14] to secure collected data by drones, they utilize the Bitcoin blockchain technology and Public Key encryption as the cryptographic algorithm. Jang *et al.* [6] do not consider the data security in their model and do not mention the packet size for the simulation. Zhou *et al.* [12] have not included fog/edge layer in their simulation and used time-consuming data securing steps in the simulation model.

III. Model Description

Adopting blockchain technology is one of the practical ways of improving scalability in the IoT framework. We develop a new comprehensive time-computation model by using the process employed in the basic IoT framework to generate a new block to a blockchain, as shown in Figure 1. We develop the following sub-computation models (corresponding to sub-section A to F in this section) to compute the total time required to generate a new block in the IoT framework.

- **A:** Layer 1, Child Sensors - Sensing, data logging, transient, data encryption, sensor delay, communication time to CH;
- **B:** Layer 2, Cluster Head (CH) - Data retrieval time from child sensors, switching, actuation, cluster data cryptographic, data processing, data communication time to fog server;
- **C:** Layer 3, Fog/Edge Computing - Data communication time from all connected CHs, data processing, blockchain data consensus process, fog layer cryptographic, data communication time to the cloud server;
- **D:** Layer 4, Cloud Server - Data communication time from fog servers in the network, cryptographic operational time, block mining processing time;
- **E:** Blockchain Network Delay - Impact of transactions queuing delay, the influence of block size on new block generation time, block mining, block propagation, and smart contract execution time.

For simplicity, we assume a linear relationship between the size of the data and the estimated time of a new block to be added to the blockchain. This linear relationship is realistic for cases when the data size is large which is the case in many IoT applications.

In this section, we propose our comprehensive model for estimating block generation time in the IoT framework. Block generation time in the IoT system should be smaller than the block interval (time) of a chosen blockchain framework in order to add IoT transactions to the blockchain. Therefore, such a comprehensive model is required to formulate the time consumption for key functions in the IoT layers (Figure 1) and next develop the total time computation model for the new block generation process in the IoT network.

A. Total Computation Time for Layer 1 (Child Sensors)

Sensor node operation is divided into several phases: (i) initializing, (ii) sensing, (iii) computing, (iv) transmitting data to the parent sensor, (v) sleeping, and (vi) waking up (for energy saving) [9]. However, encryption and delay time should be added to the existing functionality. The timing is divided into wake-up time, active time, sleep time, transient time, data encryption time, and delay. The sensor performs its functions as rounds. During a lifetime of a sensor, it can perform several rounds of functions that repeat the phases from (i) to (vi) in each round. The total time taken to sense and identify a single transaction is the sum of each phase in a single round (Figure 1).

Different sensors behave in different ways depending on the sensor type, where different time slots are required to conduct the same function based on the data type. For example, the sensing time for a humidity sensor is less than the time required for a visual sensor used for image processing.

Consider Layer 1 has n child sensors designated $1, 2, \ldots, n$, where $L_1 = \{1, 2, \ldots, n\}$. Next, we identify the time required to complete each sensor function (Layer 1) in detail for sensing time, sensor data logging time, sensor data encryption time, sensor delay time, data communication time to CH, and total child sensor computation time.

a) Sensing time (t_{ts}): The principal function of the sensor is to sense the conditions of an environmental phenomenon and transmit data to parent nodes. The time taken to sense 1 bit of data is considered as t_{s_1}. The total time taken to sense b_1 bits, t_{ts} is given by

$$t_{ts} = b_1 t_{s_1}. \tag{1}$$

b) Sensor Data logging time (t_{dl}): The sensed data is logged into the sensor memory. The time required to read and write b_1 bits of data, t_{dl} is given by

$$t_{dl} = b_1(t_w + t_r) \tag{2}$$

where t_r and t_w represent the time taken for reading and writing bit data.

c) Sensor Transient time (t_{tr}): To save battery power and as an energy-saving mechanism, sensors transit to sleep mode every milli/microsecond (depending on the application) after an active period. Therefore, they spend time to transit between operation modes such as active, sleep, and idle. For a single transaction, the transient time t_{tr} is a combination of sleep time and the active time given by

$$t_{tr} = t_{off} + t_{on} \tag{3}$$

where t_{off} is the sleep time, and t_{on} is the active time.

d) Sensor Data encryption time (t_e): Data encryption t_e is performed before transmitting to ensure security during the communication via the network. Encryption time varies depending on the sensor voltage, as explained by Yuan and Qu [28], and the data packet size. For b_1 data, the sensor data encryption time is given by

$$t_e = b_1 t_{ek} \tag{4}$$

where t_{ek} is the time to encrypt 1 bit of data.

e) Sensor delay time (t_{lt}): The delay of the data communication between sensor nodes is derived as the sum of the few different factors named: (i) sender processing delay t_{ls}, (ii) media access delay (contention delay) t_{lm}, (iii) receiver processing time t_{lr}, (iv) radio propagation time t_{lp}, and (v) network traffic t_{tf} [29]. Therefore, we determine the maximum delay in transmitting a data packet t_{lt}

$$t_{lt} = t_{ls} + t_{lm} + t_{lr} + t_{lp} + t_{tf}. \tag{5}$$

f) Data communication time to CH (t_{tm}): After receiving data, it is communicated/transmitted to the associated parent node for further analysis. We estimate the time required to transmit b_1 bits data, t_{tm}

$$t_{tm} = b_1 t_d + t_{lt} + \tau_1 \tag{6}$$

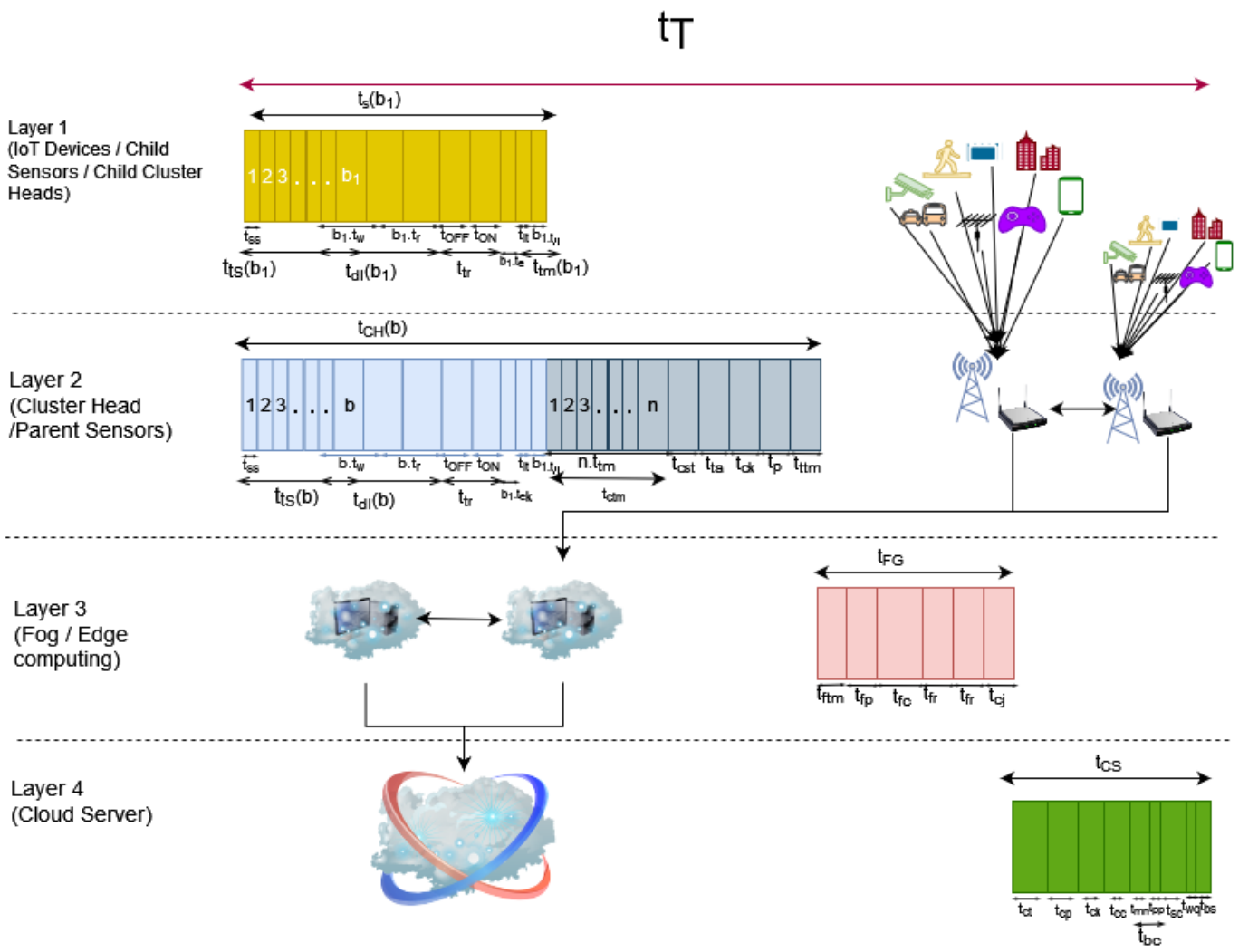


Fig. 1. Basic IoT architecture with four layers (IoT devices/sensors, CH layer, fog/edge layer, and the cloud service) and key functions of each layer (IoT devices/sensors, CH layer (parent sensors), fog/edge layer, and the cloud service) corresponding to equations (1) - (28).

where t_d is the time required to transmit 1 bit of data, t_{lt} is the delay time, and τ_1 is a random delay during the data communication time to CH.

g) Total child sensor computation time for Layer 1: (t_s) Sensors in a network have different behaviors and performances. For example, the time needed to process an image is more than the time required to process temperature data. Therefore, the maximum time taken for sensor functioning should be computed. We quantify the time to sense and complete a single transaction by a child sensor t_s

$$t_s = t_{ts} + t_{dl} + t_{tr} + t_e + t_{lt} + t_{tm}. \tag{7}$$

B. Total Computation Time for Layer 2 (Cluster Head (CH))

CH performs sensor functionality similar to the (low-powered) child sensors. It has sensing time, data logging time, transient time, and data communication time similar to other sensors mentioned in Section III-A. Additionally, the specific functions of the CHs are (i) retrieving data from child sensors, (ii) switching between microcontroller processing and events, (iii) performing data encryption and decryption, (iv) triggering physical events (actuating), (v) transmitting data to the next layer.

Consider Layer 2 with m CHs designated $1, 2, \ldots, m$, where $L_2 = \{1, 2, \ldots, m\}$. Next, we explain the time required to complete each additional function illustrated in Figure 1 performed in the CH in detail.

a) Data retrieval time from child sensors (t_{ctm}): Due to limited hardware capabilities and the network traffic in the sensor network, each child sensor is assigned a separate time slot to transmit their packets to the parent sensor using Time Division Multiple Access (TDMA) method [30]. It is assumed that all child sensor nodes in the cluster (Figure 1) transmit their data to the CH asynchronously by utilizing the TDMA mechanism. Therefore, we compute the total time required to transmit data from child sensors, t_{ctm} to CH

$$t_{ctm}(i) = \sum_{i=1}^{m} t_{tm(i)} + \tau_2 \tag{8}$$

where t_{tm} is the data communication time to CH and τ_2 is a random delay during the data retrieval time from child sensors.

b) Switching Time (t_{cst}): The time required for sensors to switch into different operational modes depends on the microcontroller processing time and the time between switching events [9]. We derive the switching time of a CH t_{cst}, to switch between the α number of microcontrollers and the β number of switching events (sensing different measurements based on the different environmental conditions such as object present or not, maximum and minimum level detection of the object)

$$t_{cst}(k,j) = \sum_{j=1}^{\alpha} t_{ct(j)} + \sum_{k=1}^{\beta} t_{se(k)} \tag{9}$$

where t_{ct} is the time required for micro-processing, and t_{se} is the time to switch between events.

c) Actuation time (t_{ta}): The CHs provide mechanical responses based on the inputs they receive, such as turning on a light and activating motor sensors. Additionally, they perform as actuators to trigger physical events based on the received values from other sensors and themselves. We derive the total actuation time to trigger the β number of events t_{ta}

$$t_{ta}(k) = \sum_{k=1}^{\beta} t_{a(k)} \tag{10}$$

where t_a is the actuation time required to trigger a single event. The time varies with the event's length, and this is used only if the sensor is an actuator.

d) Cluster data cryptographic time (t_{ck}): Encrypted data sent by the child nodes are decrypted and processed by the CH and encrypted again prior to the transmission to the fog layer. We estimate the total time taken to the encryption and decryption process in CH t_{ck}, is defined by

$$t_{ck} = (b_1 + b_2)(t_{ek} + t_{dk}) \tag{11}$$

where t_{ek} is the sensor encryption time and t_{dk} is the decryption time for 1 bit.

e) Data processing time (t_p): Data for a single transaction is transmitted to a CH from multiple child sensors. CH uses data fusion mechanisms and rules to deliver reliable and accurate information to the next layer [31]. It is assumed that the time taken for data processing in CH is t_p. The time depends on the data type and the application requirements.

f) Data communication time to fog server (t_{ttm}): Time taken to transmit data to the fog layer from the CH is measured as t_{ttm}. The communication time depends on the data volume transferred to the next layer.

As illustrated in Figure 2, the study considers that the number of data packets transferred from the n number of child sensors is different from the sizes of data packets transferred from the respective CH. Since the CH is more powerful than child sensors, it can transmit more data. Similarly, different percentages of data are transferred to the next layer from each available cluster in the sensor network. Furthermore, the transmission of data packets between CH and the fog layer is delayed due to network delay. Therefore, we estimate the total time required to transmit CH data to the fog server

$$t_{ttm} = \max_{n \in L_1} \left([b_2 + nb_1 q] P t_{\mu} + t_{lt} \right) \tag{12}$$

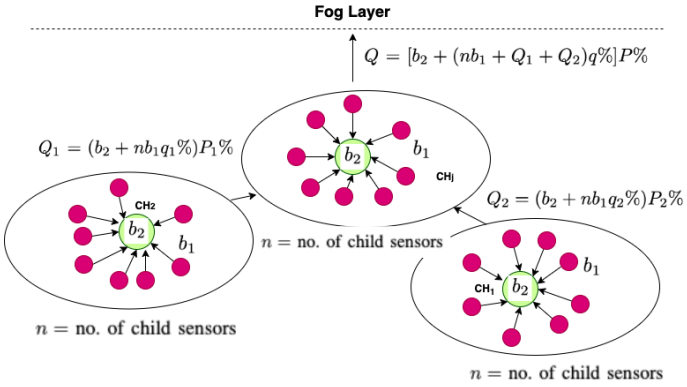


Fig. 2. Data communication or transmission flow in Cluster Network: $Q_1, Q_2, \ldots, Q_\sigma$ are the number of data packets transferred from each cluster to their parent CH, q is the percentage of total data sending to the next CH layer from each cluster, and P is the total percentage of data transmitted to the fog layer, n is the number of sensors in each cluster, b_1 is the data transferred from child sensor, and b_2 is the data transmitted from the CH. Here $Q_1 = (b_2 + nb_1q_1)P_1\%$ and $Q_2 = (b_2 + nb_1q_2)P_2\%$, hence, $Q = [b_2 + (nb_1 + Q_1 + Q_2)q]P\%$.

where b_1 and b_2 represent the number of data packets transmitted from a child sensor and CH, q and P represent the percentages of transferred data from each child sensor and CH, t_{μ} is the communication time for one packet of data to the fog layer, and t_{lt} is the network delay.

g) The total data computation time of a cluster (t_{CH}): By combining equations retrieved for child sensors and the CH, we compute the total time consumed by CH to complete a transaction t_{CH}

$$\begin{aligned} t_{CH}(i,j,k) = {} & t_{ts} + t_{dl} + t_{tr} + t_{ctm}(i) + t_{cst}(j,k) \\ & + t_{ta}(k) + t_{ck} + t_p + t_{ttm}. \end{aligned} \tag{13}$$

h) Total processing time of the sensor network (t_{tsn1}): We explore two models in this study to access t_{tsn1} that we use in the simulations. One model considers one layer of child sensor propagation and the other model considers multiple layers (2 or more) of child sensor propagation. A sensor network consists of multiple CH with subordinate child sensors as given in Figure 2 that function all together to succeed in the data tracking process. Therefore, if the topology in Figure 2 is used for the network, the total processing time of the sensor network t_{tsn1} is equal to the maximum time taken to process all CHs, and we estimate it

$$\begin{aligned} t_{tsn1}(i,j,k) = {} & \max_{m \in L_1, L_2} \; t_{SN} + t_{ctm}(i) + t_{cst}(j,k) \\ & + t_{ta}(k) + t_{ck} + t_p + t_{ttm}. \end{aligned} \tag{14}$$

where $\max_{m \in L_1, L_2} \; t_{SN} = \max(t_{ts}) + \max(t_{dl}) + \max(t_{tr})$. If a different topology is used with σ cluster layers before transmitting data to the fog layer as given in Figure 2, we determine, $t_{tsn\sigma}$

$$\begin{aligned} t_{tsn\sigma}(i,j,k,v) = {} & \max_{m \in L_2} \; t_{tsn1}(i,j,k) \\ & + \sum_{v=1}^{\sigma} (b_2 + (b_1 n + Q_v) q P t_v) \end{aligned} \tag{15}$$

where $Q_1, Q_2, \ldots, Q_\sigma$ are measures transferred from each cluster to their parent CH, t_v is the data communication time from the v^{th} child layer to its parent layer, q is the percentage of total data sending to the next CH layer from each cluster, and P is the total percentage of data transmitted to the fog layer. Depending on the sensor network (IoT) structure, we can use either Equation (14) or Equation (15). However, for simplicity, in this study, we use Equation (14).

C. Total Computation Time for Layer 3 (Fog/Edge Computing)

The fog/edge layer assists the IoT framework by conducting communication, routing, storage, and computation [32]. Data received from CHs are analyzed using fog computing before sending the final value to the cloud service. Furthermore, since some IoT sensors are unable to process raw data, the fog layer aids in improving the efficiency of the transaction [11]. In this study, five main functions of the fog server are considered: (i) data gathering from all associated CHs, (ii) data processing, (iii) blockchain validation process, (iv) data decryption and encryption, (v) data communication or transmission to cloud server.

Consider Layer 3 with r fog nodes designated $1, 2, \ldots, r$, where $L_3 = 1, 2, \ldots, r$. Next, we describe the time required to complete each function in the fog layer.

a) Data communication time from all connected CHs (t_{ftm}):

To evaluate t_{ftm}, we consider communication delays in all three layers as follows.

1) Sensor Layer - (i) sender processing delay t_{ls}, (ii) media access delay (contention delay) t_{lm}, (iii) receiver processing time t_{lr}, (iv) radio propagation time t_{lp}, and (v) network traffic t_{tf} and random delay (τ_1 and τ_2) during the data communication time
2) Fog Layer - network delay, random delay
3) Cloud Layer - network delay, transactions queuing delay.

The fog server receives values from different CHs to perform analysis and other functionalities. Due to the synchronized data receiving capability of the fog layer, we estimate the total time required to transmit data from multiple CHs, t_{ftm}

$$t_{ftm} = \max_{m \in L_2} t_{ttm} \tag{16}$$

where data t_{ttm} is the data communication time from the CH to the fog layer.

b) Data processing time (t_{fp}): When the fog node successfully retrieves values, it starts processing the transaction data to generate information. For example, when multiple sensors sense the temperature from a large area and send values to different CHs, those CHs send finalized values to the fog nodes based on their received information. The time consumption for data processing time is measured as t_{fp}, and it depends on the number of transactions and data amount to be processed.

c) Time for the blockchain data consensus process (t_{fc}): It is essential to follow a consensus mechanism for data before adding a new transaction to the existing blockchain [10]. The different blockchain frameworks follow different mechanisms to validate the new transactions to mitigate different types of attacks. Different blockchain types have different mechanisms for performing the consensus process. For instance, *bitcoin* utilizes the Proof of Work (PoW) system, *Ethereum* uses PoW and PoS (Proof of Stake), and *Hyperledger Fabric* utilizes Byzantine Fault Tolerance (BFT) as their consensus algorithms [33]. The total consensus time depends on the selected blockchain type. Here we suggest performing a consensus process in the fog/edge layer to improve the total performance of the cloud layer. The advances in effective resource management in the fog layer can enhance the reliability of cloud facilities by minimizing process latency. The consensus time of a transaction to validate h bytes of data in the fog server t_{fc} is measured by

$$t_{fc} = h t_{fh} \tag{17}$$

where t_{fh} is the time required to process the consensus mechanism for the 1 byte of data (1 byte = 8 bits).

d) Fog layer cryptographic time (t_{fk}): The fog layer performs the cryptographic process to decrypt data sent by sensors and encrypt them before sending it to cloud service. The time to encrypt and decrypt a file depends on the file size and the cipher algorithm [34]. Therefore, we determine the time required to encrypt and decrypt h bytes of data, t_{fk}

$$t_{fk} = h(t_{fe} + t_{fd}) \tag{18}$$

where t_{fe} and t_{fd} represent the time taken to encrypt and decrypt 1 byte of data using desired ciphertext length.

e) Data communication time to the cloud server (t_{cj}): If the transaction is accepted by the validation process of the fog layer, it is transmitted to the cloud server, which is the highest layer of the IoT framework. We evaluate the total time to transmit data to the cloud, t_{cj}

$$t_{cj} = \max_{r \in L_3} (t_{ft} + t_{fl}) \tag{19}$$

where t_{ft} is the time to transmit h bytes from the fog layer to the cloud server, and t_{fl} is the network delay.

f) Total fog/edge: server processing time (t_{FG}) From the combinations of the equations in the section, we add together the total time consumption in the fog layer t_{FG}

$$t_{FG} = t_{ftm} + t_{fp} + t_{fc} + t_{fk} + t_{cj}. \tag{20}$$

D. Total Computation Time for Layer 4 (Cloud Server)

The cloud server, the final layer of the IoT platform, is used as the main block management network in blockchain technology. It acts as the final layer with (i) final data validation with other cloud servers, (ii) block mining, and (iii) block propagation activities in the blockchain.

Consider Layer 4 with s cloud servers designated $1, 2, \ldots, s$, where $L_4 = 1, 2, \ldots, s$. Next, we explain the time required to complete each sub-function in the cloud.

a) Data communication time from fog servers in the network (t_{ct}): Since different fog networks are connected to a single cloud service, a cloud server receives data from multiple fog layers for a transaction. Therefore, we quantify the cloud has to wait until all fog servers finish transmitting data, t_{ct}

$$t_{ct} = \max_{r \in L_3} t_{cj} \tag{21}$$

where t_{cj} is the data communication time to the cloud.

b) Cryptographic operational time (t_{ck}): We estimate Time taken to encrypt and decrypt δ MB data in the cloud server t_{ck}

$$t_{ck} = \delta(t_{ce} + t_{cd}) \tag{22}$$

where t_{ce} and t_{cd} represent the time required to encrypt and decrypt 1 MB data in the cloud.

c) Total cloud computation time (t_{CS}): From the combinations of the equations in the section, we derive the total time consumption in the cloud t_{CS} to generate a single block

$$t_{CS} = t_{ct} + t_{ck}. \tag{23}$$

E. Computation Time for Blockchain Network Layer (t_{bc})

The IoT data layer sends transactions to the blockchain network layer. The application layer is in charge of data processing and end-user service delivery. The Blockchain network layer maintains the blockchain while interacting with the application layer in both directions. We compute the time required for this process.

a) Impact of Transactions Queuing Delay in $M/D/1$ Queue Model for Blockchain-based IoT Network (t_D): It is likely that, in some cases, new transactions arrive before the previous transactions are served and added to the blockchain. Therefore, a buffer is used to store transactions waiting to be connected to the blockchain. We model the waiting time in the queue (including the service time) of transactions (t_D) to join the blockchain using queuing theory and select the $M/D/1$ queueing model.

The assumption that arriving transactions follow a Poisson process (M) is justified by the fact that these transactions are generated by many independent users. Because blockchain transactions are processed normally one at a time by a server, the single server assumption is justified. In our model, we assume for simplicity that the service time — specifically, the time taken to add a transaction to a given blockchain — is fixed (deterministic).

This assumption is grounded on several reasons: In many IoT applications, the size and complexity of transactions are approximately fixed, especially when devices are programmed to send standardized data packets required for adding transactions to a blockchain at regular intervals [35], [36]. While IoT networks can experience congestion, many real-time critical IoT applications are designed to operate under controlled network conditions, reducing the variability in transaction processing times [37]. For IoT applications requiring high real-time performance, the network and devices often use optimized protocols and infrastructures to ensure minimal required delay [38]. Therefore, while there might be slight fluctuations in service times, we can approximate them as deterministic for our analysis.

It is crucial to note that while our model adopts this deterministic assumption for simplicity, in practice, service times can vary based on numerous factors. Future work may explore stochastic models to account for such possible variability.

In addition, the assumptions of unlimited buffer and first-in-first-out (FIFO) scheduling are also consistent with blockchain practice. Although, in practice, the arrival rate over time may vary, our implied assumption of a constant arrival rate is overcome in this paper by considering different levels of queue utilization.

Let λ be the transaction arrival rate (transactions per second), μ be the service rate (transactions per second), and ρ be the queue utilization factor, where $\rho = \lambda/\mu$. As shown in [39], the mean transactions queuing delay in the system of the $M/D/1$ queue is given by

$$t_D = \frac{1}{2\mu} \times \frac{2-\rho}{1-\rho}. \tag{24}$$

b) Influence of Block Size on New Block Generation Time (t_{bs}): The capacity of a block or a block size is equal to the amount of data it can hold. A block, like any other container, may only hold a certain amount of data or transactions in the context of our work. Once a transaction is accepted after the mining process, the accepted transactions are ordered and packed into a block. Thus, the number of transactions that can fit into one block depends on the block size. Block sizes are limited on different blockchains. For example, the average block size is up to 4 MB for *Avalanche* and *Polkadot*, 2 MB for *Bitcoin, Conflux*, and *Binance*, 1 MB for *Hyperledger Fabric, Litecoin, EOS*, and *Dogecoin*, 20-30 kB for *Ethereum*. Additionally, some transactions are lightweight. Let s_b be the block size in MB, s_t the transaction size in MB, n_t the number of pending transactions to be added to a block, and μ the transactions per second [tps]. As the ratio s_b/s_t is the number of transactions required per block and n_t/μ is one transaction time, we evaluate the time to create one complete block t_{bs}

$$t_{bs} = \frac{s_b}{s_t} \times \frac{n_t}{\mu}. \tag{25}$$

c) Total block mining time: (t_{mn}) An existing blockchain is updated using two phases named block mining t_{mn} and block propagation. The time it takes for miners or validators in a blockchain network to validate transactions within a single block is known as mining time. Block generation (creation), validation, and integration to the transaction of the existing blockchain are termed block mining [40]. The time required for block mining in blockchain-based IoT systems can be influenced by various factors, including the specifics of the transaction and the role of centralized systems like the cloud layer. However, the mining process fundamentally relies on the consensus mechanism adopted by the blockchain and the collective efforts of participating nodes. Therefore time to mine a block is measured by t_{mn}, which depends on the number of transactions x [15] in the blockchain.

d) Block propagation time (t_{pp}): Block propagation time is a well-known barrier in blockchains that prohibits any blockchain framework from scaling. Stale blocks are mine blocks that are excluded from the main chain due to simultaneous transactions, conflicts, or network propagation delays. The block propagation time is an essential factor influencing a blockchain framework's scalability and stale block rate. When a block is added to an existing blockchain, it is broadcasted via the entire network to reach most network nodes using a suitable propagation mechanism. The average time it takes for

a new block to reach the majority of nodes in a network is called block propagation time.

The research revealed that extended propagation delay could lower a node's ability to withstand 51% attacks and selfish mining attacks. Blockchain developers aim to minimize block propagation time to mitigate this security issue, typically targeting it to be less than 1% of the average block time [41]. Therefore, although for some blockchain frameworks, this target has not yet been achieved, in this study, we use this 1% target to calculate the block propagation time in cases where more reliable data on block propagation time is unavailable. Due to fluctuations in network conditions, the median block propagation time may not be consistently accurate.

e) Smart contract execution time (t_{sc}): We assume each blockchain has a designated target smart contract function which the submitter always signs. As a result of processing the transactions submitted by users, the blockchain node executes a smart contract. The transaction is submitted to any blockchain node responsible for distributing that to the entire blockchain network. After the transaction is distributed, it is processed by each node using the executable program in the target smart contract. We determine the time taken to execute the smart contract t_{sc}.

f) Total blockchain time (t_{bc}): We derive the total time to update the existing blockchain t_{bc}

$$t_{bc} = t_D + t_{bs} + t_{mn} + t_{pp} + t_{sc}. \tag{26}$$

F. Total Computation Time Required to Generate a New Block in the IoT Framework

From the combination of equations (7), (13), (20), (23), (24), and (26), we compute the total computation time to sense an environmental phenomenon until it generates as a new block to an existing blockchain in the IoT platform t_T

$$\begin{aligned} t_T(i,j,k) = \max_{m \in L_1, L_2} \; & t_{SN} + t_{ctm}(i) + t_{cst}(j,k) + t_{ta}(k) \\ & + t_{ck} + t_p + t_{ttm} + t_{ftm} + t_{fp} + t_{fc} + t_{fk} \\ & + t_{cj} + t_{ct} + t_{ck} + t_D + t_{bs} + t_{mn} + t_{pp} + t_{sc}. \end{aligned} \tag{27}$$

From the summations of equations (1) – (26), we further simplify the total computation time (27) as

$$t_T(i,j,k) = \underbrace{\max(b_1 t_s) + \max(b_1(t_w + t_r)) + \max(t_{off} + t_{on})}_{Layer\ 1\ \&\ Layer\ 2\ (Sensor,\ CH)} + \underbrace{\sum_{i=1}^{m} b_1 t_d(i) + t_{lt}(i) + \tau_1(i) + \tau_2 + \sum_{j=1}^{\alpha} t_{ct(j)} + \sum_{k=1}^{\beta} t_{se(k)}}_{Layer\ 2\ (Cluster\ Head,\ CH)} \tag{28}$$

$$= \underbrace{+ \sum_{k=1}^{\beta} t_{a(k)} + (b_1 + b_2)(t_{ek} + t_{dk}) + t_p + \max_{n \in L_1} ([b_2 + n b_1 q] P t_\mu + t_{lt})}_{Layer\ 2\ (Cluster\ Head,\ CH)}$$

$$= \underbrace{+ \max_{m \in L_2} \; t_{ttm} + t_{fp} + h t_{fh} + h(t_{fe} + t_{fd}) + \max_{r \in L_3} (t_{ft} + t_{fl})}_{Layer\ 3\ (Fog/Edge\ Computing)}$$

$$= \underbrace{+ \max_{r \in L_3} \; t_{cj} + \delta(t_{ce} + t_{cd})}_{Layer\ 4\ (Cloud\ Service)} + \underbrace{\left(\frac{1}{2\mu} \times \frac{2-\rho}{1-\rho}\right) + \left(\frac{s_b}{s_t} \times \frac{n_t}{\mu}\right) + t_{mn} + t_{pp} + t_{sc}.}_{Blockchain\ Network\ Layer}$$

Thus, this is the estimated time required to generate a new block in the blockchain-enabled internet of things (IoT).

G. Requirement for a New Block Generation Time for IoT

Once we obtain the total computation time to sense an environmental phenomenon until it generates a new block to an existing blockchain in the IoT platform, we need to observe which blockchain platform is suitable for the specific IoT applications. To add the IoT transactions to the blockchain, block generation time in the IoT should be less than the block interval (time) of a particular blockchain framework. Hence, we obtain the comparison

$$\text{Block generation time in IoT}(t_T) < \text{Block interval (time)}. \tag{29}$$

Depending on the application requirements (such as smart agriculture, smart home, and smart transportation system), users could choose the suitable blockchain framework type using the proposed model.

IV. Simulation Design

A simulation is carried out to evaluate the proposed model. The analysis is performed using MATLAB (MathWorks Inc., Natick, MA, USA) R2021b on a computer with macOS Monterey with Processor 2 GHz Quad-Core Intel Core i5 and RAM (Random Access Memory) 16 GB 3733 MHz LPDDR4X. All parameter values used for the simulation model are presented in Table II. The experimental values we use in this analysis are taken from peer-reviewed literature. Hence, we believe our results represent a general IoT setup.

A sensor network is used with 100 sensor nodes that are connected to their respective CHs, and the same simulation settings utilized in [9] are applied for the sensor network. It

is assumed that all connected child sensors are homogeneous and take a similar time to transmit data to the respective CH. The sensor network we consider in our simulation consists of powerful CHs, fixed clusters, and single-hop transmission. Using the above simulation settings, we generate 1,000,000 random setups, enabling each simulation data point to obtain 1,000,000 random setups. Depending on the IoT application (or use case), we can determine how many hours/days the simulation will run. IoT in agriculture, collects data from sensors every hour, whereas IoT in smart cities collects data every two minutes.

The fog and cloud simulation setup used is similar to the simulation conducted by Naas *et al.* [8]. The size of data packets generated is assumed to be increased by 10 percent in each subsequent layer due to the added overheads (that is, if the sensor generates 1 kB data packet, the fog layer adds an overhead of 100 bytes). Moreover, we assume that the network is a permissioned network which increases the security of the block generation process. We use *Ethereum, Hyperledger Fabric, Algorand, Conflux, Polkadot*, and *Avalanche* blockchain for the simulation model. As the experiments performed by Gervais *et al.* [16] and Malik *et al.* [46] the respective median block propagation times in seconds are 1.02, 0.85, 0.5-0.75, and 0.075. Furthermore, to ensure data security, we consider the data encryption algorithms, such as *Advanced Encryption Standard (AES), Data Encryption Standard (DES), Triple DES (DES3), Rivest Cipher 2 (RC2), Rivest Cipher 6 (RC6), Blowfish, 256-bit ECC (elliptic curve cryptography), 2048-bit RAS (Rivest-Shamir-Adleman)* and *RAS-3072* in the study.

V. Results

This study illustrates the general taxonomy of a blockchain-enabled IoT system and its contribution to the overall data acquisition delay. We develop a model to determine key time-consuming areas of the IoT network to generate a new block in an existing blockchain. A new, comprehensive, time utilization model is essential for the IoT network to improve process efficiency and scalability. The applicability of the proposed model is validated through simulation experiments. We compare the total block generation time with the different blockchain frameworks and data encryption algorithms in the simulation process. Some blockchain frameworks do not provide block propagation time, hence they cannot be used to compare performance. Nevertheless, the IoT issues that affect delay are applicable to other blockchains, so we use blockchains for which data is available. In addition, we analyze the time consumption of each IoT layer to identify each layer's contribution to the total block generation process. In the simulation process, we utilize the fog layer for the block validation process to improve the efficiency of the cloud server and the total block generation process in the IoT network. The results indicate that the total block generation time varies depending on the selected IoT framework, data encryption algorithm, blockchain type, and key functions of the layers. Finally, we compare the outcome of our model with similar time computation models developed by Jang *et al.* [6], Liang *et al.* [14], and Zhou *et al.* [12] to identify the efficiency of our model.

TABLE II
Parameter Values for the Simulation Model

Sym	Description	Value
b_1	Packet size transmit from child sensor	1 kB
b_2	CH communication or transmission packet size	2 kB
n	Number of child sensors in a cluster	100
β	Number of switching events in a sensor	1
α	Number of microcontrollers in a sensor	1
l	Number of validation cycles	1
q	Data percentage from sensors to fog	70%
P	Total data percentage to fog	80%
h	Data packet size in the fog layer	10 kB
δ	Data packet size in the cloud server	100 kB
t_s	Sensor sensing time	0.0002 ms [9]
t_{ek}	Sensor encryption time (AES)	0.7346 ms [34]
t_{dk}	Sensor decryption time (AES)	1.2857 ms [34]
t_w	Sensor data writing time	0.00645 ms [9]
t_r	Sensor data reading time	0.0003 ms [9]
τ_1	Random delay (Layer 2 - CHs)	vary
τ_2	Random delay (Layer 1 - Child sensors)	vary
t_{lr}	Sensor propagation delay time	0.002 ms [17]
t_{ls}	Sensor processing delay for communication	0.0006 ms [18]
t_d	Data transmit time to CH	0.0002 ms [29]
t_{lm}	Media access delay	0.0001 ms
t_{lp}	Receiver processing delay after data receiving	0.0006 ms [18]
t_{tf}	Network traffic	0.0002 ms
t_{on}	Transient time to switch on	2.45 ms [9]
t_{off}	Transient time to switch off	0.25 ms [9]
t_{ct}	Microcontroller processing time	0.0001 ms
t_{se}	Switching time between different events	0.002 ms [42]
t_a	Actuation time	0.0025 ms [19]
t_p	Data processing time of CH	0.14 ms [20]
t_{fl}	Network delay in fog	1.41 ms [23]
t_μ	Data communication or transmission to fog	0.0006 ms [24]
t_{fp}	Data processing time of fog	23.36 sec [7]
t_{dp}	Data processing time of cloud	84.58 sec [7]
t_{fh}	Data validation in own memory	0.0014 ms [25]
t_{fe}	Fog layer encryption 100 kB (AES)	73.469 ms [34]
t_{fd}	Fog layer decryption 100 kB (AES)	116.32 ms [34]
t_{ft}	Data communication or transmission time from fog to cloud	9.01 ms [8]
t_{bv}	Data validation time in cloud	0.17 ms [8]
t_{cn}	Network delay of the cloud server	17.99 ms [23]
t_{ce}	Encryption time in the cloud 1MB (AES)	187.12 ms [34]
t_{cd}	Decryption time in the cloud 1 MB (AES)	120.82 ms [34]
μ	Service rate in the queue (transactions per second, tps)	20 (*Ethereum*) [43], 3500 (*HyperLedger Fabric*) [44], up to 4500 (Avalanche) [45]
n_t	Number of pending transactions	100 Tx
s_t	Average transaction size	380.04 bytes
s_b	Block size	$\approx$ 20 KB - 2 MB
t_{pp}	Median block propagation time	Refer Table VIII

A. Overall New Block Generation Time Based on the Blockchain Type

Block time or block processing time is the time length it necessitates to create a new block or the time it carries to mine a block or file in a blockchain. Block processing time is the actual time within a network to validate transactions for one block and add a new block to the blockchain. Based on the blockchain type, the different blockchain frameworks take different times (see Table VII and Table VIII in Appendix). The blockchain framework decides block interval time; for example, the estimated block time in *Bitcoin* is 10 minutes, whereas *Ethereum*'s is between 10 and 19 seconds. Since the Bitcoin blockchain framework is computationally expensive and requires high bandwidth overhead and delays, it may not be suitable for most IoT applications. Further, it is well known that in Bitcoin, new blocks of size approximately 1 megabyte are mined every 10 minutes on average. Thus, the available data rate is about 6 megabytes/hour, 100 kilobytes/minute, or 1.67 kilobytes/second. This is well below the speed of most wireless communication technologies available today. Hence, it is not possible for an IoT system that would generate data at this rate. Thus, we remove the Bitcoin blockchain from our analysis.

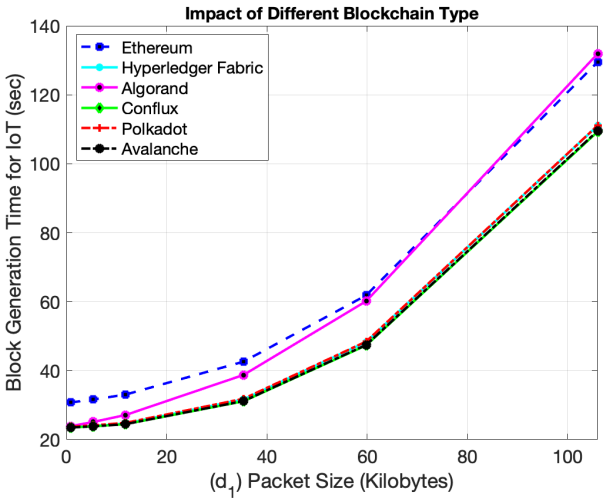


Fig. 3. Average block generation time versus data packet size for different blockchain types.

The simulation is conducted to measure the overall block preparation time with the identified functions. The initial results show that cryptographic time and block mining time utilize the maximum time consumption of the IoT block generation process. Therefore, firstly, we observe the most appropriate blockchain type for the IoT network.

Few key blockchain frameworks, such as *Ethereum, Hyperledger Fabric, Algorand Conflux, Polkadot*, and *Avalanche* are associated with the simulation (Figure 3). We compare a small number of blockchain frameworks because the median block propagation time (Equation (26)) for all blockchain systems was not provided. In contrast, the blockchain framework does not play a significant role in block generation time for smaller data packets. The most evident result of the analysis is that the block processing time in the IoT network is less than the block interval times of the given blockchain types when the data packet size is below 110 kB.

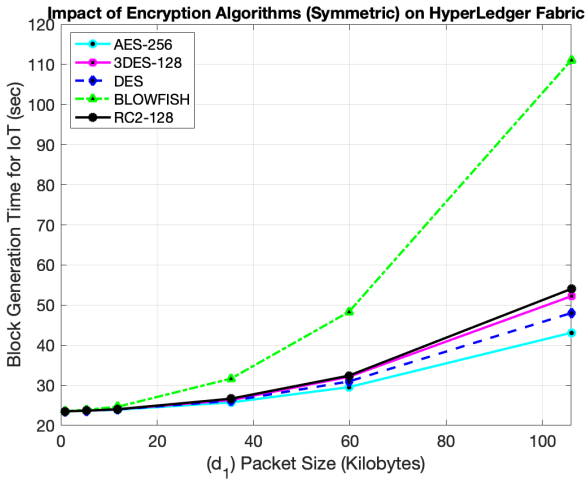
Figure 3 indicates that *Avalanche* has the shortest block processing time. Due to the real-time decision-making requirements of the IoT network, it is essential to provide the information and decisions immediately to the end user. Therefore, in the results, it is observed that *Avalanche, Hyperledger Fabric, Conflux*, and *Polkadot* are the most time-efficient blockchain types for the IoT network.

B. Overall New Block Generation Time Based on Encryption Algorithm

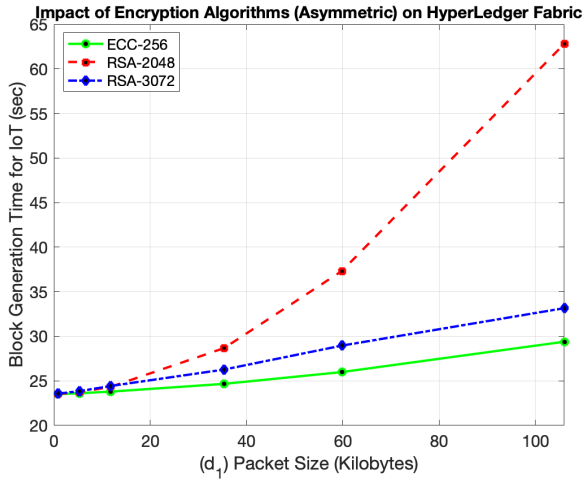
Since encryption helps secure information and sensitive data and can improve the security of communication between client applications and servers, the efficiency of encryption algorithms has been extensively studied. Further, the encryption time will account for a significant portion of the total time spent on the block creation process. As a result, it is critical to thoroughly research and analyze encryption algorithms in order to choose the appropriate blockchain framework.

When considering the time taken to process data encryption, it is understandable that the selected algorithm affects the total block generation time (Figure 4). The results show that the total time is increased from 1.2 - 4.3 sec based on the selected algorithm type. However, as illustrated in Figures 4(a) *HyperLedger Fabric* (for symmetric encryption) and 4(b) (for asymmetric encryption), no significant differences are found between the seven algorithm types when the data packet size is below 5 kB. The most striking observation to emerge from the data comparison is that the processing time of each algorithm varies with the packet size after 35 kB. This observation could be due to the performance factors of each algorithm. Furthermore, in a typical IoT network, the fog and cloud layers process more data volume than the sensor layers. Therefore, the data packet size of each layer should be analyzed before incorporating an algorithm in a specific layer. These findings suggest that the block processing time AES and ECC are the time-efficient algorithms for real-time data security in the IoT framework when data packet size is up to 110 kilobytes.

The RSA (Rivest-Shamir-Adleman) and elliptic curve encryption are two of the world's extensively utilized asymmetric algorithms. Because of the limitations of experimental data on the time taken to process data encryption for different data sizes, we limit the complete analysis of all algorithms to 200 kilobytes. The ECC-256 and RAS-2048 show the lowest block time. Hence, in addition to another popular encryption algorithm, AES, we further observe these three encryption algorithms with four different blockchain frameworks (*Hyperledger Fabric, Algorand, Conflux, Polkadot, Avalanche*) as shown in Figure 5 and Figure 6. Significant differences are observed between asymmetric (AES versus BLOWFISH) and asymmetric (ECC-256 versus RAS-2048) algorithms for block generation time.

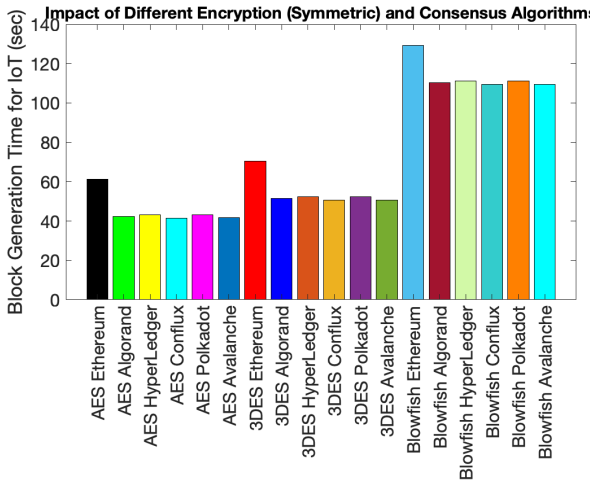


(a) Different cryptographic algorithms (symmetric) for *HyperLedger Fabric*.

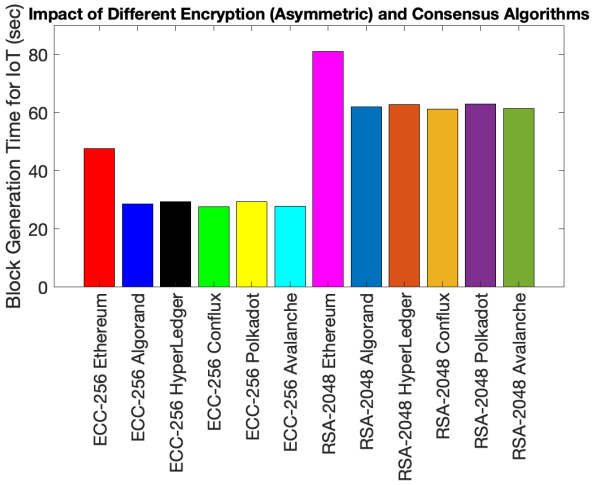


(b) Different cryptographic algorithms (asymmetric) for *HyperLedger Fabric*.

Fig. 4. Average block generation time versus data packet size for different cryptographic algorithms for *HyperLedger Fabric*.



(a) Different symmetric (AES, 3-DES, Blowfish) encryption algorithms.



(b) Different asymmetric (ECC-256, RSA-2048) encryption algorithms.

Fig. 5. Average block generation time using different symmetric (AES, 3-DES, Blowfish) and asymmetric encryption algorithms (ECC-256, RSA-2048) and blockchain frameworks (*Ethereum, Algorand, HyperLedger, Conflux, Polkadot, Avalanche*).

C. Overall New Block Generation Time Based on the IoT Layers (Sensor, Fog/Edge, Cloud)

In general, Layer 3 (fog/edge layer) assists in reducing the network latency of the IoT network by bearing the additional burden from the cloud server. Further, in our model, the fog layer has been utilized to perform the blockchain consensus process to minimize the block execution time of the cloud. Typically block the validation process is conducted in the cloud server, and it takes much time because of the high network latency in the cloud server. Therefore, we propose to utilize the fog layer for that to accelerate the block generation process. Figure 7 illustrates the average processing time versus the data packet size in each IoT layer. In addition to utilizing the fog layer to bear the additional burden from the cloud server, we use it to perform the blockchain consensus process to minimize the block execution time of the cloud. As a consequence, we observe lower block generation time in the cloud layer than in the fog layer.

It is essential to observe the block generation time comparison with/without the fog/edge layer and with/without the cloud layer for the blockchain-enabled IoT networks. Thus, Figure 8 shows a block generation time comparison for 100 kB data packets. We consider two scenarios: fog only and cloud only, and then compute the time using our proposed model of the block time required by each scenario. In the first scenario (fog only) block time takes 20-40 sec while in the second scenario (cloud only) it takes around 85-100 sec. Therefore, the results of our study confirm that if we use only cloud servers, the block generation time is doubled compared to using fog servers only.

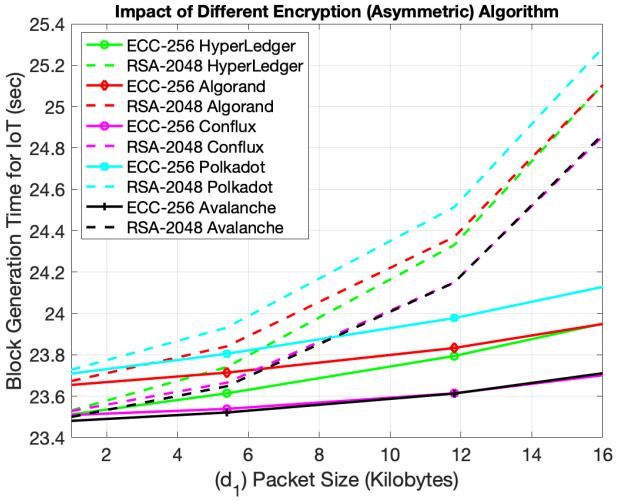


Fig. 6. Average block generation time using different encryption algorithms (ECC-256, RSA-2048) and blockchain frameworks (*HyperLedger, Algorand, Conflux, Polkadot, Avalanche*).

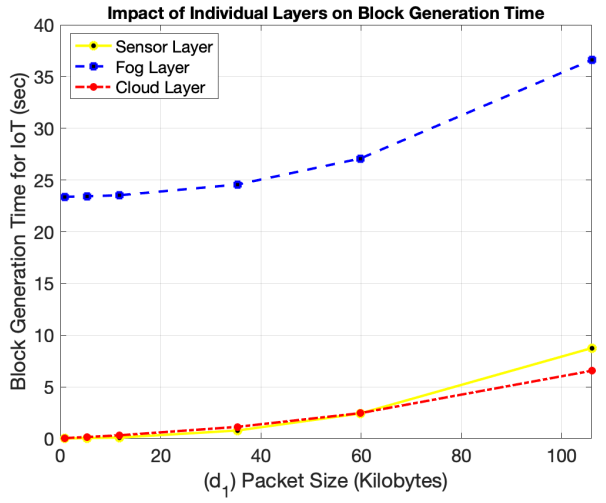


Fig. 7. Block generation time comparison between different IoT layers.

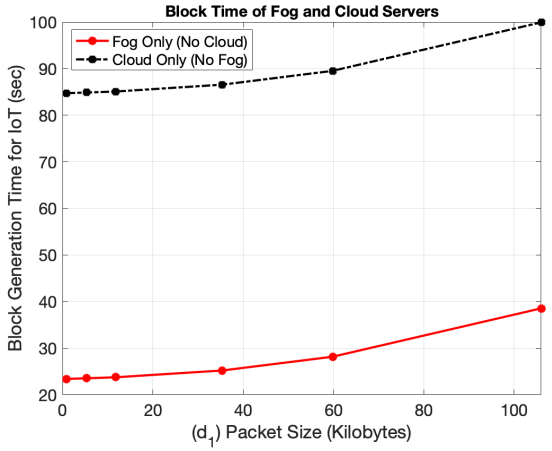


Fig. 8. Simulation results for block generation time comparison between fog and cloud servers.

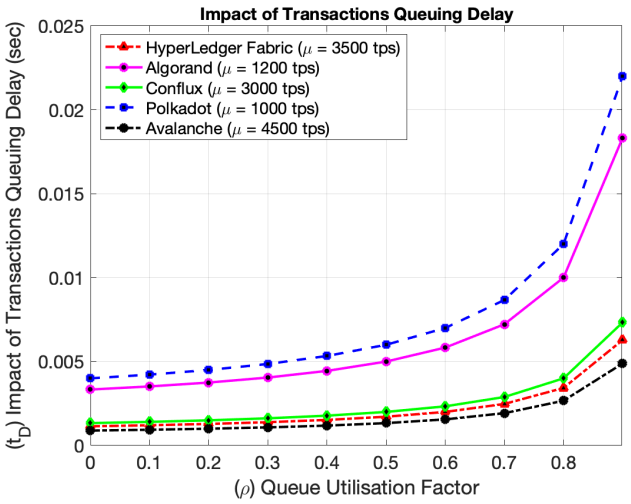


Fig. 9. Transactions mean queuing delay (D) for different queue utilization factor values (ρ) in $M/D/1$ queue model for blockchain-based IoT network (*HyperLedger, Algorand, Conflux, Polkadot, Avalanche*).

D. Overall New Block Generation Time Based on the Transactions Queuing Delay

We apply the $M/D/1$ queue model to our blockchain-based IoT context. Figure 9 shows the impact of queuing delay of transactions (t_D) for different queue utilization factors (ρ) using Equation (24).

However, we observe that the queuing time is negligible relative to the block time in the IoT network (Figure 10). In addition, this demonstrates the impact of the transaction queuing delay (t_D) for different queue utilization factor values (ρ) is higher in *Polkadot*, while the overall block time is lower in *Conflux* and *Avalanche*.

E. New Block Generation Time Based on the Block Size

Figure 11 shows the block time versus block size when the device processing speed is 2 GHz using Equation (25). For all blockchain platforms, block time increases as block size grows. However, since block sizes are not likely to significantly exceed 2.5 MB, the maximum increase that we observe is below 0.06 seconds and therefore this increase due to block size is insignificant relative to the block time in the IoT network.

F. Overall New Block Generation Time: Performance Evaluation Comparison

Next, we compare our model with similar time computation models developed by Jang *et al.* [6], Liang *et al.* [14], and Zhou *et al.* [12]. Various attempts to measure block generation time have been presented in Table III and Figure 12 with a summary of their considerations, such as the IoT layers,

TABLE III
COMPARISON OF PERFORMANCE EVALUATION

Model	Packet Size	Total Time (sec)	Blockchain Type	Security	Device	CH	Fog/Edge	Cloud
Our model	1024 bytes	0.495	*Hyperledger Fabric* (BFT)	DES	Yes	Yes	Yes	Yes
Jang *et al.* [6]	Not Mentioned	4.665	*Hyperledger Fabric* (BFT)	Not Given	Yes	No	Yes	Yes
Zhou *et al.* [12]	1014 bytes	7.3	*Ethereum* (PoW)	ECIES, ECDSA	Yes	No	No	Yes
Liang *et al.* [14]	1000 bytes	2.9	*Bitcoin* (PoW)	PK cryptography	Yes	No	No	Yes

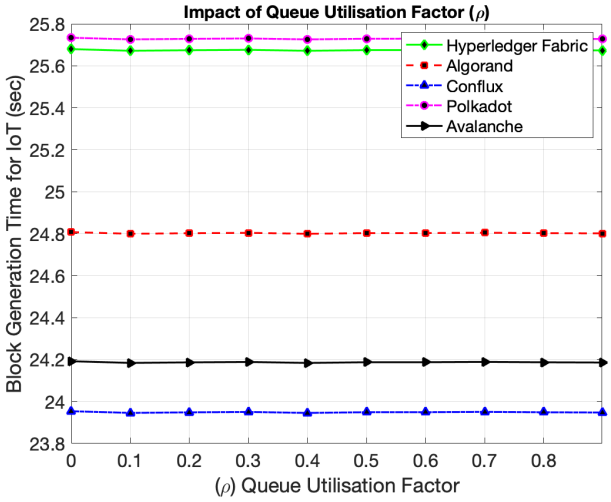


Fig. 10. Comparison of the block generation time for different queue utilization factor values (ρ) for *HyperLedger, Algorand, Conflux, Polkadot* and *Avalanche*.

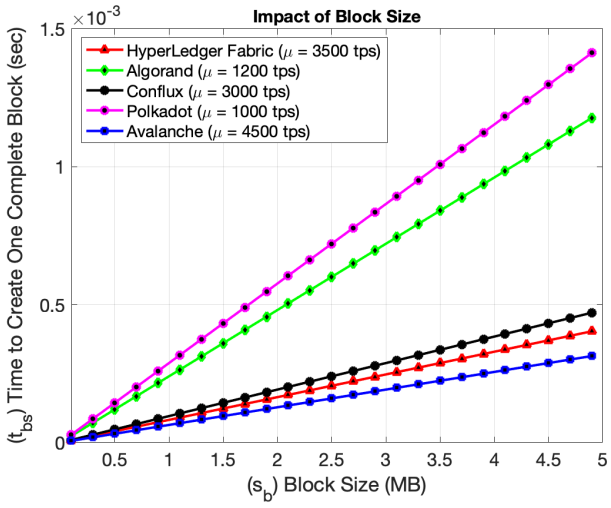


Fig. 11. Comparison of the block generation time for different block size (ρ) for *HyperLedger, Algorand, Conflux, Polkadot* and *Avalanche*, when device processing speed is 2 GHz.

security mechanism, and the used blockchain type. However, their results are not very encouraging. Without considering the time taken for each function, findings cannot be utilized for accurate decision-making. Moreover, compared to the time of those models, our model has taken the best time consumption

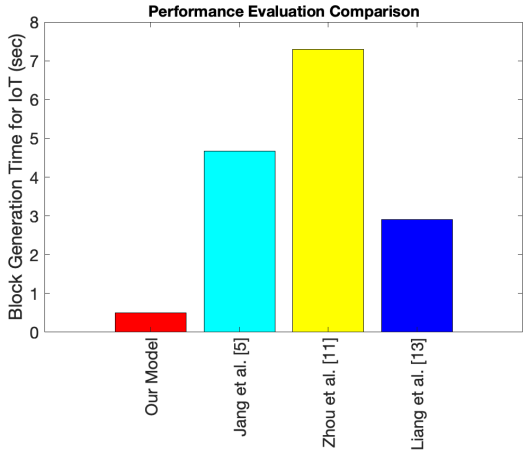


Fig. 12. Various attempts to measure block generation time comparison between different studies.

approach with a total processing time of 0.495 sec. Finally, we verify that unnecessary time consumption can be eliminated by utilizing an appropriate blockchain framework, encryption algorithm, and fog layer.

G. Real Blockchain Data Comparison for the Different Blockchain Frameworks

The block size limit refers to the maximum amount of data that a blockchain block may carry. The maximum block size determines the number of transactions taken inside a block. This size consequently controls the throughput of the system. In addition, larger block sizes bring slow block propagation speeds; thus, expanding the old block rate or stale block rate, which impacts the blockchain network's security. Observing the impact of block size on the scalability and security of the blockchain is, hence, essential. In addition, it is vital to understand the current market of blockchain technology and cryptocurrency. Thus, we compare actual blockchain data using [47] (*accessed April 2022*) for different blockchain frameworks. Since there is a vast range of values, we use the logarithmic scale (log scale) to demonstrate values.

Figure 13 shows block size in kilobytes and the number of transactions per day in mega (10^6) from June 2020 to May 2021 for *Ethereum, Dogecoin, Ripple (XRP)*, and *Litecoin*. *Ethereum* and *Litecoin* show the largest block sizes. Thus, we further investigate the number of transactions of each framework. As block sizes are large in *Ethereum* and *Litecoin*, obviously, those can carry more transactions. On top of that, we compare block time in minutes and the number of transac-

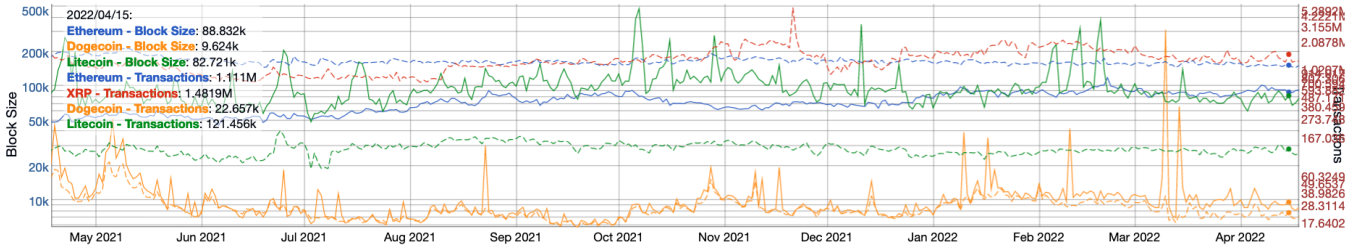


Fig. 13. Real blockchain data comparison: Block size and the number of transactions for the different blockchain framework - *Ethereum, Dogecoin, Ripple* (*XRP*), and *Litecoin* for May 2021 to April 2022.

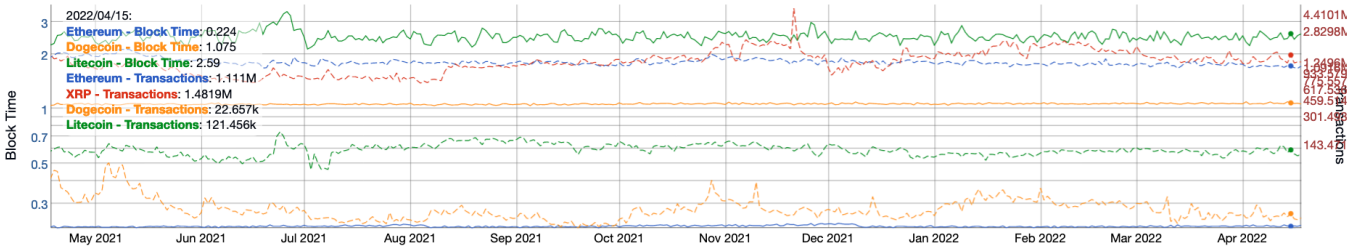


Fig. 14. Real blockchain data comparison: Block time and the number of transactions for the different blockchain framework - *Ethereum, Dogecoin, Ripple* (*XRP*), and *Litecoin* for May 2021 to April 2022.

tions per day in mega (Figure 14) *Ethereum* and *Ripple* show very low block time. We repeated the all above simulations for *Ethereum, Hyperledger Fabric, Algorand, Conflux, Polkadot* and *Avalanche* and found the results to be consistent.

VI. Discussion

Combining blockchain and IoT/Edge technology can provide trusted access and control [3] to the network and to storage facilities. It also enables distributed computing at the edge, high-efficiency computation, large-scale network facilities, and data storage while preserving blockchain security.

A comprehensive understanding of the general functions and their time consumption is an immense advantage for any application to achieve maximum efficiency. The present study is designed to determine key time-consuming areas of the IoT network while adding a block to an existing blockchain. Our study compares the total block generation time with different blockchain frameworks and data encryption algorithms. In addition, the average time consumption comparison of each layer and fog layer utilization for the block validation process can be considered as another significant instance. The results of the study indicate that the total block generation time varies depending on the selected IoT framework, data encryption algorithm, blockchain type, and key functions of the layers.

In this study, first, we analyze all significant functions performed in each IoT layer, and next, we measure the time taken for each function to identify the respective data processing time of those. One of the key findings of the study is identifying the time taken for key activities in the sensor network (sensor layer and CH layer). The findings for sensor behavior are primarily similar to the prior study done by Halgamuge *et al.* [9]. They have conducted their study to estimate sensor energy consumption by identifying key sensor and CH functions. However, data cryptography and network latency functions are not included in their model. Furthermore, that study was mainly focused on energy consumption and optimization. In contrast, we mainly focus on the time consumption in our model to generate a new block in the IoT network.

As another key finding in this study, we propose that the fog layer can perform a block validation process. It will assist in reducing the heavy load of the cloud layer. Several prior studies are focused on using the fog/edge layer as an intermediate layer in the IoT platform to reduce the additional burden of the cloud layer [8], [23], [24]. However, using fog/edge in the blockchain-enabled IoT architecture is not adequately investigated. Therefore, the outcome of the simulation assists future studies in using fog in the blockchain paradigm.

This study indicates that a few appropriate blockchain types to generate a new block in the IoT platform are *Avalanche, Conflux, Algorand, Polkadot* and *Hyperledger Fabric*. The block generation time in the IoT is less than the block interval time of the blockchain frameworks such as *Ethereum*. Moreover, due to the high data generation rate and real-time decision-making requirements in the IoT network, they cannot be used in the IoT network.

Some distributed blockchains, such as *Bitcoin, Ethereum, Hyperledger Fabric, Algorand, Conflux, Avalanche, Polkadot, Cardano, EOS, NEO,* and *Litecoin*, are permissionless, allowing any node to participate in the consensus process. *Hyperledger Fabric* is a permissioned blockchain; thus, it is not vulnerable to diverging ledgers ("fork"). The Orderer is in charge of packaging transactions into blocks and distributing them around the network to anchor peers who are in charge of peer discovery. Additionally, Hyperledger Fabric uses an Orderer (also known as an "Ordering node") that does this transaction ordering, which forms an ordering service along with the other Orderer nodes. Fabric's design uses determin-

TABLE IV
COMPARISON OF DIFFERENT ENCRYPTION ALGORITHMS

Encryption Algorithm)	**DES**	**3DES (3-DES, TDEA)**	**AES**	**BLOWFISH**	**RC2 (Rivest Cipher 2)**	RC6 (Rivest Cipher 6)	**ECC-256**	**RSA-2048**	**RSA-3072**	**International Data Encryption Algorithm (IDEA)**
Year	1977	1978	2000	1993	19987	1998	1985	1978	1978	1991
Organisation / Developer	IBM and US government	IBM	National Institute of Standards and Technology (NIST)	Bruce Schneier (Harvard University)	Ron Rivest (MIT University)	Ron Rivest (MIT University)	Neal Koblitz (University of Washington) and Victor Miller (IBM)	Rivest-Shamir-Adleman	Rivest-Shamir-Adleman	Lai and Massey (ETH Zurich)
Country	USA	USA	Belgium	USA	USA	USA	USA	USA	USA	Switzerland
Key Structure	Symmetric Key	Symmetric Key	Symmetric Key	Symmetric Key	Symmetric Key	Symmetric Key	Asymmetric Key (public and private keys)	Asymmetric Key (public and private keys)	Asymmetric Key (public and private keys)	Symmetric Key
Type/Block Size (bits)	64-bit block cipher	64-bit block cipher	128-bit block cipher	64-bit block cipher	64-bit block cipher	128-bit block cipher	64-bit block cipher	112 bits	128 bits	64-bit block cipher
Key Length/Size (bits)	56	56, 112, 168	128, 192, 256	32-488 (variable)	8-128	128, 192, 256	256-384	2048	3072	128
Number of Rounds	16	48	10 for 128, 12 for 192, 14 for 256	16	16	20	1	1	1	8.5
Number of Operations per Round	16, 20	20	16	20	20	36	1	1	1	16
Encryption Time for 915 KB (sec)	15.19	45.75	4.75	15.19	24.68	29.43	1.79	120.13	201.14	11.96
Algorithm Structure	Feistel network	Feistel network	Substitution and permutation network	Feistel network	Feistel stream	Feistel network	Public key algorithm	Factorisation	Factorisation	Lai–Massey scheme
Authentication	Message authentication code (MAC)	Message authentication code (MAC)	Message authentication code (MAC)	Message authentication code (MAC)	Message authentication code (MAC)	Message authentication code (MAC)	Digital signature	Digital signature	Digital signature	Message authentication code (MAC)
Key Compromise Option	Both sender and receiver side	Both sender and receiver side	Both sender and receiver side	Both sender and receiver side	Both sender and receiver side	Both sender and receiver side	Only owner of asymmetric key	Only owner of asymmetric key	Only owner of asymmetric key	Both sender and receiver side
Known Attacks	Brute force attack, man-in-the-middle attack	Brute force attack, Chosen plaintext attack, known plaintext attack	Side channel attack	Dictionary attack, birthday attack	Differential attack, linear attack	Brute force attack, analytical attack, correlation attack	Side channel attack, backdoor attack, quantum computing attack	Brute force attack, oracle attack, man-in-the-middle attack, side channel analysis attack, power fault attack	Brute force attack, oracle attack, man-in-the-middle attack, side channel analysis attack, power fault attack	Linear attack
Encryption Speed	Very slow	Very slow	Faster	Fast	Slow	Slow	Fast	Average	Average	Fast
Security Level	Proven in adequate	Adequate	Excellent	Good	Adequate	Good	Excellent	Good	Good	Good

istic consensus techniques, ensuring that each block certified by a peer is final and correct.

In the computation (2nd, 3rd, and 4th generation) blockchain frameworks on the market may support IoT applications with smart contracts. NEO [48], Cardano [49], EOS [50], R3 Corda [51], Binance (BNB) [52], Polkadot [53], Avalanche [45], Algorand [54] and Conflux [55] are a few examples.

Compared to blockchain, platforms based on DAG utilize a different ledger structure and different methods for transaction confirmation. Thus, an extension of this work for all IOTA versions is considered as future work.

Data security is one of the essential and challenging constraints associated with the IoT platform. In contrast, most of the studies ignore adhering to security procedures in their experiments and mention it as a challenge [10]. Even though blockchain has an in-built security procedure, it has been vulnerable to several attacks in the past decade [56]. Data security should be a predominant factor of any reliable electronic system when managing sensitive consumer data (such as smart health monitoring applications). Therefore, the most appropriate mechanism to preserve data within a network is using an encryption algorithm to convert plain text to ciphertext during communication. Based on that fact, we simulate different encryption algorithms to identify the most efficient algorithm for the block generation process in the IoT network.

Additionally, we observe that 256-bit ECC (elliptic curve cryptography) has the potential to be the most efficient encryption algorithm for IoT networks to enhance the performance and scalability of the block generation process. However, the robustness of the encryption algorithm depends upon the type of cryptography, key management, number of keys, and number of bits used in a key. Longer key length and data length provides high security; on the other hand, they consume more power and result in more heat dissipation. This provides the trade-off between security level and power consumption. In addition, keys with more bits utilize more computation time to encrypt data. Table IV shows this comparison for different encryption algorithms.

In the computation of the encryption time, a standard assumption is made regarding uniform hardware and software

implementation, ensuring consistent processing power across different devices. Nevertheless, it is essential to acknowledge that real-world encryption speeds may differ due to discrepancies in hardware specifications, software configurations, and implementation difficulties. In our calculations, we adopt a processing speed of 2 GHz and allocate 1 GB of RAM as the basis for our estimations.

To estimate the encryption time (Table IV), we employ the following equations: Time per block: calculates the number of rounds and operations per round: Time per block = Number of rounds × (Number of operations per round / Processing speed); Number of blocks: calculates the total number of blocks needed to encrypt the data: Number of blocks = Data size / Block size; Time taken to encrypt: combines the number of blocks and the time per block to determine the overall encryption time: Time taken to encrypt = (Number of blocks × Time per block). These equations provide a general framework for estimating the encryption time based on the given assumptions. However, it is essential to consider that actual encryption speeds may vary due to several factors, including algorithmic efficiency, hardware capabilities, and software optimizations. The comparison and the findings of the study will assist future studies in improving their models by considering security principles.

Since crypto-currencies process a few transactions per second, the theoretical limit is usually in the low two- or three-digit range, approximately for *Ethereum*, 15-20 tps, and for *Bitcoin*, 7 tps. The parameters primarily determine the average block time, maximum block size, and minimum transaction size [57]. In practice, we cannot increase the block size. When the block size is large, it takes a long time to propagate a new block to all nodes through the wireless blockchain network. This impacts the latency and security of the network. Besides, every device may not have high network bandwidth and sufficient hardware storage capacity on top of the computation power. Thus, high demands could lead to sacrificing blockchain decentralization, which is the blockchain trilemma. On the other hand, with the advancement of technology, the future device storage capacities (hard disks) and network speed remain to grow globally; thus, larger block sizes might be convincing in the future. If network speed and storage capacities continue to enhance, a noticeable increment in block sizes may be convincing in the future. That allows high transaction rates (tps) without a notable rise in energy consumption [58]; thus, the scalability of the network will be improved.

Jang *et al.* [6], Liang *et al.* [14], and Zhou *et al.* [12] simulate sample modules to generate a block using the IoT architecture. However, to obtain accurate decision-making in an IoT environment, the time taken for each function is essential. For example, Jang *et al.* [6] ignored CH layer, Zhou *et al.* [12] and Liang *et al.* [14] ignored CH and Fog/Edge layers. Therefore, it is essential to provide all required parameters used in any experiments or simulations. Jang *et al.* did not consider the data security in their model and did not mention the packet size they used for their experiment. Compared to the time of those models (Jang *et al.* [6] 4.66 sec, Zhou *et al.* [12] 7.3 sec and Liang *et al.* [14] 2.9 sec), our model has taken the best time consumption approach with a total processing time of 0.495 sec. These were the main limitations of their work. In addition, we validate that by utilizing an appropriate blockchain framework, encryption algorithm, and edge/fog layer, unnecessary time consumption can be eliminated. While we present one of the prevalent IoT architectures, it is essential to note that not all IoT implementations mandate every layer discussed. Indeed, in certain contexts, IoT services can be effectively deployed and utilized within local networks or intranets.

The most exciting finding was that we observed the block generation time comparison with/without the fog/edge layer and with/without the cloud layer for the blockchain-enabled IoT networks. The results of our study confirm that if we use only cloud servers, the block generation time is doubled compared to using fog servers only. These findings of the current study are consistent with those of Gill *et al.* (2019) [7] who found the vision of fog computing and experimentally found a complement to cloud computing and an essential ingredient of the IoT. Moreover, they compared by considering different configurations (CPU GHz, RAM size, and power). Thus, based on our analysis, we can suggest that if the network uses small data packets, it is recommended to use fog or edge computing because of the network's efficiency (low latency, low data processing time).

In reviewing the recent literature, most of the studies have considered limited functional areas of the IoT platform to increase the data processing efficiency. So far, however, there has been little discussion about individual layer functions, and no study can be found with a comprehensive-time utilization model related to the block generation process. Without having a clear picture of process functions and respective time consumption, it is difficult to identify how those improvements impact the total block generation process. Therefore, the findings in this study have several important implications for future practices. In future investigations, it might be possible to use different data packet sizes to observe the evaluations of the estimated impact. Thus, it is essential to verify the proposed model in an industrial IoT cloud and fog computing environment for practical understanding. Fog computing does not substitute the cloud but rather complements it [59]. Fog computing can work with cloud computing for the blockchain-enabled IoT. Cloud computing will be the primary force to be considered with the IoT, Big Data, Artificial Intelligence (AI), and future technologies. Thus, we recommend combining fog and cloud for the blockchain-enabled IoT depending on the requirements, such as limited scalability, less data storage, and computation capabilities.

In recent years, various blockchain technologies have been explored for integration with IoT applications, aiming to strengthen security, transparency, and decentralized control. The popularity of blockchain-based IoT may vary over time and depend on specific use cases. In this study, we use a few blockchain types to generate a new block in the IoT platform: Avalanche, Conflux, Algorand, Polkadot, and Hyperledger Fabric. Table V provides an overview of the blockchain platforms utilized in IoT applications, detailing their unique features and relevance to the domain.

TABLE V
OVERVIEW OF BLOCKCHAIN PLATFORMS IN IOT

Platform	Blockchain Overview and External Perspectives
Ethereum	Originally designed as a general-purpose platform for decentralized applications; Ethereum's smart contract capabilities have made it a popular choice for IoT solutions, particularly in scenarios requiring programmable logic embedded within transactions [12], [16], [60].
Hyperledger Fabric	Developed under the Linux Foundation's Hyperledger project, Hyperledger Fabric is a modular and flexible blockchain platform. Tailored for specific enterprise needs, it is a favored platform for IoT solutions in industries such as supply chain and healthcare [6], [33].
Algorand	Known for its high throughput and low latency, Algorand's consensus mechanism offers potential for large-scale IoT networks requiring real-time data processing [61], [62].
Conflux	Utilizing a unique Tree-Graph consensus mechanism, Conflux targets both scalability and security. It is a promising blockchain for IoT applications with extensive networks [61], [63].
Polkadot	Polkadot's multi-chain structure emphasizes high scalability, interchain operability, and flexible governance. It is suitable for diverse IoT applications that communicate across multiple blockchains [61].
Avalanche	With a goal of creating highly scalable decentralized networks, Avalanche's subnetworks and custom virtual machines make it a robust choice for complex IoT ecosystems [60].

A. Possible Applications (Use Cases)

We use a few case studies to demonstrate the usefulness of the suggested model in this sub-section. A wide range of businesses, in addition to financial institutions, have planned to explore the blockchain's capabilities. IoT devices may use blockchain to enhance security and transparency in their ecosystems. In several Blockchain Enterprise applications, it has been demonstrated that merging IoT and Blockchain can have a substantial benefit in a variety of industries. A few examples follow.

1) Energy Trading: blockchain plays an essential role in energy trade for IoT applications [26].
2) Supply Chain and Logistics: The effectiveness of a supply chain is dependent on trust among the various stakeholders. The combination of blockchain and IoT technologies can help to improve the traceability and dependability of data along the chain [64] and end-to-end visibility.
3) Smart Homes: Smart IoT-enabled devices are becoming increasingly vital in our daily lives. The IoT blockchain allows home security systems to be controlled remotely using a smartphone. Telstra, an Australian telecommunications corporation, has used blockchain and biometric security to protect data collected by smart devices [65].
4) Agriculture: Pavo marketplace [66] is a blockchain IoT use case that delivers transparency to farmers by offering a new and smart farming technique. Pavo's IoT hardware device, which is put on farms, collects data that is kept on the blockchain. It allows farmers to improve their agricultural operations by analyzing the data collected.

B. Comparing Use Cases: Evaluating Model Applicability

To justify various design choices of our experiments, in this subsection, we present two different case studies that contrast the sensor data collection intervals in IoT applications for agriculture and smart cities. We assume a higher frequency of data collection in smart cities allows for more real-time monitoring and rapid response to changing conditions. At the same time, agricultural IoT applications generally require less frequent data collection due to the nature of their use cases.

Block time refers to the average time it takes to create a new block in a blockchain. To calculate the appropriate block time for each use case, we need to consider the data collection frequency, the number of sensors, and the blockchain's capacity to store the data. We assume that each data point requires the same storage space. We determine the appropriate block time by assuming that the blockchain can accommodate the storage capacity required for each use case.

For each use case, we perform the activities below:

- Step 1: Get the total number of deployed sensors count.
- Step 2: Calculate the total data points per day for each sensor.
- Step 3: Calculate the data points generated per block time.
- Step 4: Calculate the storage capacity required.
- Step 5: Determine the appropriate block time, assuming the blockchain can accommodate the required storage capacity.
- Step 6: Calculate the maximum data points stored in a block for each blockchain framework.

To compare various design choices of our experiments, we compare two blockchain frameworks (Hyperledger Fabric, Avalanche) using two use cases (IoT in agriculture, IoT in smart cities) (Table VI). Note that in certain applications, as discussed (see Table VI), such as within the healthcare domain, data might be collected at frequencies as low as one data point per second.

C. Limitations of the Model

Like any model, the proposed model has some limitations. This information would help to estimate the time to generate a new block.

1) Constraints of the design - our research mainly focuses on the given IoT layer structure; however, the layers could be vary in a real-world context.
2) Sampling errors could occur - data we use from previous studies may not reflect the general population or appropriate population concerned.
3) Simulation data - data for simulation are collected from different previous studies. Thus, when considering all data in a single flow, the results could deviate from the actual.
4) Measured timing could be changed on other dependencies (performance of hardware, software).

TABLE VI
COMPARING USE CASES: CASE STUDY 1 - IOT IN AGRICULTURE AND CASE STUDY 2 - IOT IN SMART CITIES

Description	Case Study 1 - IoT in Agriculture	Case Study 2 - IoT in Smart Cities
IoT environment context	A farm utilizes IoT sensors to monitor the temperature, humidity, and soil moisture across different sections of the field. These sensors collect hourly data, allowing the farm to respond to environmental changes and optimize crop management. A blockchain network is implemented on the farm to ensure data security and integrity of the data.	A smart city uses IoT sensors to monitor traffic flow, air quality, and energy consumption across different areas of the city. These sensors collect data every two minutes, allowing the city to respond quickly to traffic patterns, pollution levels, and power usage changes. This real-time data collection helps the city efficiently manage resources and improve the quality of life for its residents. A blockchain network is deployed on the IoT smart city to enhance data security and maintain the integrity of the collected information.
IoT environmental parameters - sensors	Temperature, humidity, light intensity, and soil moisture	Traffic management, air quality monitoring, noise level, and energy consumption tracking
Number of sensors deployed	50	200
Data collection frequency	Every 60 mins (hourly)	Every 2 mins
Total data points per day for each sensor	24 hours/day $\times$ 1 data point/hour = 24 data points	24 hours/day $\times$ 30 data points/hour = 720 data points
Total data points collected by all sensors in a day	50 sensors $\times$ 24 data points = 1200 data points	200 sensors $\times$ 720 data points = 144,000 data points
Number of data points generated within the desired block time.	50 data points	200 data points
Storage capacity required per block time by assuming that each data point requires 1 KB of storage	50 data points $\times$ 1 KB = 50 KB	6000 data points $\times$ 1 KB = 6,000 KB
Calculate the maximum data points that can be stored in a block for Hyperledger Fabric (1 MB block size = 1024 KB)	1024 KB / 1 KB = 1024 data points	1024 KB / 1 KB = 1024 data points
Calculate the maximum data points that can be stored in a block for Avalanche (4 MB block size = 4096 KB)	4096 KB / 1 KB = 4096 data points	4096 KB / 1 KB = 4096 data points
New block generation time using Hyperledger Fabric (1 MB block size)	Data points generated per 60 minutes: 60 minutes $\times$ (50 data points / 1024 max data points) = 2.929 minutes (approx.)	Data points generated per 2 minutes: 2 minutes $\times$ (6,000 data points / 1024 max data points) = 1.71minutes (approx.)
New block generation time using Avalanche (4 MB block size)	Data points generated per 60 minutes: 60 minutes $\times$ (50 data points / 4096 max data points) = 0.73 minutes (approx.)	Data points generated per 2 minutes: 2 minutes $\times$ (6,000 data points / 4096 max data points) = 0.296 minutes (approx.)

5) Proposed model is generated using the common functions of the process; however, those could be slightly changed based on the devices used (e.g., different sensors and hardware).
6) This study does not differentiate the communication approach devices use to transmit data (e.g., Bluetooth or WiFi). However, communication may be interfered with or depends on this in the real world.
7) The median block propagation time for all blockchain frameworks was not given; thus, we use a limited number of blockchains for the comparison.

VII. FUTURE DIRECTIONS

Current security technologies are unable to keep up with the exponential expansion in the number of Internet-connected devices and their CPU and memory constraints, resulting in vulnerabilities for hackers to exploit. IoT/Edge computing can increase the amount of resources and services available at the network's edge. However, distributed nodes pose a security concern. Despite its widespread application in various fields, AI remains a single source for building black boxes for consumers, limiting their trust in its outcome. In government and industry, federated databases are becoming more widespread. Optimizing federated-AI model adaptation

for on-the-fly IoT/Edge data and leveraging Federated-AI for blockchain scalability and interoperability is an exciting potential future research avenue.

In the future, researchers could explore the feasibility and implications of executing all described operations on a local blockchain, where a single device carries out all processes. This exploration could open new avenues for efficient IoT implementations and further promote advancements in this direction.

In this work, quantum cryptography's effects on the future of encryption were not examined, again, because of the unavailability of data. However, as with any other new technology, as data becomes available, it can be incorporated into our model.

The Digital twin is a representation of a physical asset, process, or service in a digital form. Directly modeling the physics of Edge/IoT networks is challenging. Automating the construction of the digital twin of Edge/IoT networks for cybersecurity monitoring and cyber threat modeling is an important future research direction. Furthermore, exploring how to combine different emerging technologies such as federated learning, artificial intelligence, and digital-twin technology with blockchain technology will be important to improve security in IoT networks.

Our model examines all functionalities in each IoT layer and presents a novel and comprehensive time estimation framework for understanding the influence of blockchain-enabled IoT on the block generation process and assessing block generation time in the IoT ecosystem. Further validation of our delay estimations of blockchain new block generation will benefit from real-world experiments utilizing various blockchain platforms.

VIII. Conclusion

This study develops a new comprehensive-time computation model for block generation in blockchain-enabled IoT and provides insights that can lead to improved scalability of the architecture. It analyzes the main functions of four IoT layers (device layer, CH layer, fog/edge layer, and cloud layer) to adapt fast, real-time, machine-to-machine communications. The evidence from this study suggests that the block generation time in IoT networks mainly depends on the blockchain type, encryption algorithm, and the efficiency of each layer. The significant findings to emerge from this study are that the block generation time can be reduced by utilizing an efficient encryption algorithm (such as 256-bit ECC, elliptic curve cryptography) and the blockchain frameworks (such as Avalanche, Conflux, Algorand, Polkadot, and Hyperledger Fabric). Nevertheless, the blockchain framework does not play a significant role in block generation time for smaller data packets. Additionally, the results of this study indicate that utilizing the fog layer for the block validation process improves the efficiency of the entire block generation process. This study could be replicated using more experimental data (encryption time for different data packet sizes) to clarify the estimated impact using a real industrial IoT environment. By employing a suitable blockchain framework, encryption algorithm, and fog layer, unnecessary time consumption can be eliminated. During the design process, the proposed tool will assist in determining the most appropriate blockchain technology for a specific use case. However, it is recommended to conduct further studies on optimizing key functions of each IoT layer to improve blockchain scalability. In particular, such optimization can be achieved through utilizing Big data analysis, Artificial Intelligence, deep learning, machine learning, federated learning techniques, and the IoT service orchestration with the block generation process.

IX. Appendix

Here, we provide Table VII and Table VIII, which were referred to in Section II, where we provide a detailed comparison of different features of blockchain frameworks to select the most efficient blockchain type.

References

[1] A. Holst, "Number of IoT connected devices worldwide 2019-2030," https://www.statista.com/statistics/1183457/iot-connected-devices-worldwide/, 2021.

[2] M. N. Halgamuge, "Optimization framework for best approver selection method (BASM) and best tip selection method (BTSM) for IOTA tangle network: Blockchain-enabled next generation industrial IoT," *Computer networks*, vol. 199, p. 108418, 2021.

[3] ——, "Estimation of the success probability of a malicious attacker on blockchain-based edge network," *Computer Networks*, vol. 219, p. 109402, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1389128622004364

[4] S. Nakamoto, "Bitcoin: A peer-to-peer electronic cash system (White Paper)," [Online] https://bitcoin.org/bitcoin.pdf, 2008.

[5] K. Panetta, "The CIO's guide to blockchain," *Smarter with Gartner*, pp. 1–8, 2018.

[6] S.-H. Jang, J. Guejong, J. Jeong, and B. Sangmin, "Fog computing architecture based blockchain for industrial IoT," in *Int. Conf. on Computational Science*. Springer, 2019, pp. 593–606.

[7] S. S. Gill, R. C. Arya, G. S. Wander, and R. Buyya, "Fog-based smart healthcare as a big data and cloud service for heart patients using IoT," in *Int. Conf. on Intelligent Data Communication Technologies and Internet of Things*. Springer, 2019, pp. 1376–1383.

[8] M. I. Naas, P. R. Parvedy, J. Boukhobza, and L. Lemarchand, "iFogStor: an IoT data placement strategy for fog infrastructure," in *IEEE 1st Int. Conf. on Fog and Edge Computing*, 2017, pp. 97–104.

[9] M. N. Halgamuge, M. Zukerman, K. Ramamohanarao, and H. L. Vu, "An estimation of sensor energy consumption," *Progress In Electromagnetics Research B*, vol. 12, pp. 259–295, 2009.

[10] S. Mondal, K. P. Wijewardena, S. Karuppuswami, N. Kriti, D. Kumar, and P. Chahal, "Blockchain inspired RFID-based information architecture for food supply chain," *IEEE Internet of Things Journal*, vol. 6, no. 3, pp. 5803–5813, 2019.

[11] S. Tuli, R. Mahmud, S. Tuli, and R. Buyya, "Fogbus: A blockchain-based lightweight framework for edge and fog computing," *Journal of Systems and Software*, 2019.

[12] L. Zhou, L. Wang, Y. Sun, and P. Lv, "Beekeeper: A blockchain-based IoT system with secure storage and homomorphic computation," *IEEE Access*, vol. 6, pp. 43 472–43 488, 2018.

[13] A. Damianou, C. M. Angelopoulos, and V. Katos, "An architecture for blockchain over edge-enabled IoT for smart circular cities," in *IEEE 15th Int. Conf. on Distributed Computing in Sensor Systems*, 2019, pp. 465–472.

[14] X. Liang, J. Zhao, S. Shetty, and D. Li, "Towards data assurance and resilience in IoT using blockchain," in *IEEE Military Communications Conf., MILCOM*, 2017, pp. 261–266.

[15] A. Lei, H. Cruickshank, Y. Cao, P. Asuquo, C. P. A. Ogah, and Z. Sun, "Blockchain-based dynamic key management for heterogeneous intelligent transportation systems," *IEEE Internet of Things Journal*, vol. 4, no. 6, pp. 1832–1843, 2017.

[16] A. Gervais, G. O. Karame, K. Wüst, V. Glykantzis, H. Ritzdorf, and S. Capkun, "On the security and performance of proof of work blockchains," in *ACM SIGSAC Conference on Computer and Communications Security*, 2016, pp. 3–16.

TABLE VII
COMPARISON OF THE DIFFERENT BLOCKCHAIN PROTOCOLS

Blockchain Framework	**Bitcoin** [4]	**Litecoin** [67]	**Ethereum** [43]	**Hyperledger Fabric** [44]	**NEO** [48]	**Cardano** [49]	**EOS** [50]	**Algorand** [54]	**Conflux** [68]	**Binance (BNB)** [52]	**Polkadot (DOT)** [53]	**Avalanche** [45]
Main Website	bitcoin.org	litecoin.org	ethereum.org	hyperledger.org	neo.org	cardano.org	eos.io	algorand.com	confluxnetwork.org	binance.com	polkadot.network	avax.network
Blockchain Generation	1st Gen	1st Gen	2nd Gen	2nd Gen	2nd Gen	1st Gen	2nd Gen	4th Gen	3rd Gen	3rd Gen	3rd Gen	4th Gen
Organisation / Devolopers	Bitcoin Foundation	Litecoin Core Development Team	Ethereum Foundation	Linux Foundation	OnChain (China's Ethereum)	Cardano Foundation, IOHK Emurgo	Block.One	Algorand, Inc.	Conflux Foundation	Binance Exchange	Web3 Foundation	Ava Labs
Governance	Bitcoin Foundation Developers Community	Litecoin Core Development Team	Ethereum Foundation Developers Community	Linux Foundation, IBM Bussiness Consortium	NEP	Cardano Foundation	EOSIO Core Arbitration Forum (ECAF)	Algorand Foundation	Conflux Foundation	Binance	Web3 Foundation	Avalanche-X Council
Established Year	2009	2011	2014	2015	2016	2017	2018	2019	2019	2020	2020	2020
Application (Use Cases)	Financial Industry	Financial Industry	Cross Industry	Cross Industry	Cross Industry	Enterprise and B2B applications	Cross Industry	Cross Industry	Cross Industry	Financial Industry	Enterprise and B2B applications	Cross Industry
Blockchain Network Type	Permissionless & Public	Permissionless & Public	Permissionless & Public or Private	Permissioned & Private	Permissionless & Public	Permissionless & Public	Permissionless & Public or Private	Permissionless & Public	Permissionless & Public	Permissionless & Public	Permissionless & Public	Permissionless & Public
Consensus Algorithm	PoW	PoW (Memory)	Proof-of-Work (PoW), Proof-of-Stake (PoS)	Practical Byzantine Fault Tolerance (PBFT), Crash Fault Tolerent (CFT), Kafka, Raft	Delegated Byzantine Fault Tolerance (dBFT), 7 validators	PoS, Ouroboros	Delegated Proof-of-Stake (DPoS)	Pure proof-of-stake (PPoS)	Tree-Graph (TG) consensus protocol (PoW)	Proof of Staked Authority (PoSA)	Nominated Proof-of-Stake (NPoS)	Avalanche consensus protocol (PoS)
Platform Description	Generic blockchain platform	Generic blockchain platform	Generic blockchain platform	Modular platform	Generic blockchain platform	Modular platform	Modular platform	Generic blockchain platform	Modular platform	Modular platform	Modular platform	Modular platform
Security (Hashing Function)	SHA 256 (SHA 2 based)	Scrypt, SHA-256	Ethash, KECCAK256, ECDSA	AES256, Nodejs Chaincode	SHA256 and RIPEMD160	BLAKE2b-256	SHA-256	Ed25519	Keccak-256 (Conflux-256), BLAKE2b	SHA-256	BLAKE2b	SipHash, SHA-256, SHA-3
Programming Language	Golang, C++	Golang, C++	Go, C++, Rust, Solidity, Serpent, LLL	Go	JAVA, C/C#	C++	C++, WASM	Reach, PyTeal, TEAL	Solidity, Rust	GO, Java, Javascript, C++, C#, Python, and Swift	JavaScript, Rust	Go, TypeScript, JavaScript, Python, Vue
Smart Contract	No (possible via sidechains)	Progress (Flare Networks)	Yes (Solidity, Vyper)	Yes (Chaincode, Golang, Node.JS, Java)	Yes (Chaincode, GO)	Yes (Plutus)	Yes (Web Assembly)	Yes (TEAL)	Yes (Solidity, Vyper)	Yes	Relay-chain, only Parachains - heterogeneous blockchains (WASM, EVM)	Yes (Solidity++, EVM, C-Chain)
Smart Contract Applications Programming Language	No	Partial	Solidity	Golang, Node.JS, Java	Chaincode, GO	Haskell (based on Plutus)	Rust, C, C++	TEAL (PyTeal)	Solidity	GO, Java, Javascript, C++, C#, Python, and Swift	WASM, EVM (only parachains)	Yes (Solidity++, EVM, X-Chain, P-Chain)
Smart Contract Execution	Native	Native	EVM	Docker	NVM	Dapps	JVM	AVM	EVM	EVM	WASM, EVM	EVM, JVM, WASM
Cross-chain Interoperability	No	No	Yes (using 3rd party solution)	No	No	Yes (using 3rd party solution)	No	No	Yes	Yes	Yes	Yes
Data Model	Transaction-based (UTXO)	Transaction-based (UTXO)	Account-based	Account-based	Account-based	Account-based	Account-based	Account-based	Account-based	Transaction-based (UTXO)	Account-based	Hybrid model (Account-based and Transaction-based(UTXO))
Currency - Native Token	Bitcoin	LTC	Ether (ETH), tokens via smart contract	None, currency and tokens via chaincode	NEO	ADA	EOS, tokens via smart contract	ALGO	CFX	BNB	DOT	AVAX
Transaction Fee	Progressively large fees	LTC	$4- $40 (GAS)	No	GAS	$0.16	0 (need bandwidth by staking)	ALGO	GAS	$0.01	No	GAS
Minning/Block Reward	Yes	Yes	Yes	Blocks are not mined - validating peers	No	Yes	Yes	No	Yes	No	Yes	Yes
Hashrate	358.331 EH/s	327.348 TH/s	613.309 TH/s	N/A	N/A	N/A	N/A	N/A	7.165 TH/s	N/A	N/A	N/A
Throughput / Scalability	7 tps	56 tps	15 - 20 tps	3.5k - 110k tps (3-4 tps)	10,000 tps	250 tps	millions	1200 tps	Up to 3000 tps	100 tps	1000 tps	Up to 4500 tps
Block Time (Interval)	10 mins (600 sec)	2.5 mins (150 sec)	12-14 sec	0.5 - 2 sec	15 sec	20 sec	0.5 sec	3.7 sec	1 sec	3 sec	7 sec	2-3 sec

TABLE VIII
COMPARISON OF THE DIFFERENT BLOCKCHAIN PROTOCOLS

Blockchain Framework	Bitcoin [4]	Litecoin [67]	Ethereum [43]	Hyperledger Fabric [44]	NEO [48]	Cardano [49]	EOS [50]	Algorand [54]	Conflux [68]	Binance (BNB) [52]	Polkadot (DOT) [53]	Avalanche [45]
Median block propagation time	8.7 sec	1.02 sec	0.5 - 0.75 sec	0.075 sec	Not Found	5 sec	Not Found	Not Found	Not Found	Not Found	Not Found	Not Found
Average Block Size	2 MB	1 MB	20-30 KB	1 MB	1-2 MB	500 KB	1 MB	N/A	Up to 2 MB	1-2 MB	3-4 MB	Up to 4 MB
Blockchain Size (Ledger Size)	402.51 GB	48.22 GB	345.17 GB	Not Found	Not Found	85 GB	Not Found	Not Found	Not Found	Not Found	Not Found	2 GB
Average Transactions per Day	256 K	30 K	1 M	5 K	4K	4K	3.5 M	5M	33K	5M	15K	2.9M
Internet of things	No (Progress)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Decentralized Finance (DeFi)	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Energy Consumption	Very High	Low	High	Low	Low	Low	Low	Low	Low	Low	Low	Low

[17] M. J. Miller and N. H. Vaidya, "A MAC protocol to reduce sensor network energy consumption using a wakeup radio," *IEEE Transactions on Mobile Computing*, vol. 4, no. 3, pp. 228–242, 2005.

[18] S. Ganeriwal, R. Kumar, and M. B. Srivastava, "Timing-sync protocol for sensor networks," in *Int. Conf. on Embedded Networked Sensor Systems*, 2003, pp. 138–149.

[19] J. Hill, R. Szewczyk, A. Woo, S. Hollar, D. Culler, and K. Pister, "System architecture directions for networked sensors," *ACM Sigplan notices*, vol. 35, no. 11, pp. 93–104, 2000.

[20] M. A. Osborne, S. J. Roberts, A. Rogers, S. D. Ramchurn, and N. R. Jennings, "Towards real-time information processing of sensor network data using computationally efficient multi-output gaussian processes," in *Int. Conf. on Information Processing in Sensor Networks*. IEEE, 2008, pp. 109–120.

[21] Z. Liao, X. Pang, J. Zhang, B. Xiong, and J. Wang, "Blockchain on security and forensics management in edge computing for iot: A comprehensive survey," *IEEE Transactions on Network and Service Management*, pp. 1–1, 2021.

[22] W. Lu, Z. Ren, J. Xu, and S. Chen, "Edge blockchain assisted lightweight privacy-preserving data aggregation for smart grid," *IEEE Transactions on Network and Service Management*, vol. 18, no. 2, pp. 1246–1259, 2021.

[23] S. Yi, Z. Hao, Z. Qin, and Q. Li, "Fog computing: Platform and applications," in *3rd IEEE Workshop on Hot Topics in Web Systems and Technologies (HotWeb)*, 2015, pp. 73–78.

[24] T. N. Gia, M. Jiang, A.-M. Rahmani, T. Westerlund, K. Mankodiya, P. Liljeberg, and H. Tenhunen, "Fog computing in body sensor networks: An energy efficient approach," in *IEEE Int. Body Sensor Network Conference*, 2015, pp. 1–7.

[25] S. Su, K. Wang, and H. S. Kim, "SmartSupply: Smart contract based validation for supply chain blockchain," in *IEEE Int. Conf. on Internet of Things (iThings)*, 2018, pp. 988–993.

[26] L. D. Nguyen, I. Leyva-Mayorga, A. N. Lewis, and P. Popovski, "Modeling and analysis of data trading on blockchain-based market in IoT networks," *IEEE Internet of Things Journal*, vol. 8, no. 8, pp. 6487–6497, 2021.

[27] R.-V. Tkachuk, D. Ilie, K. Tutschku, and R. Robert, "A survey on blockchain-based telecommunication services marketplaces," *IEEE Transactions on Network and Service Management*, pp. 1–1, 2021.

[28] L. Yuan and G. Qu, "Design space exploration for energy-efficient secure sensor network," in *IEEE Int. Conf. on Application-Specific Systems, Architectures, and Processors*, 2002, pp. 88–97.

[29] S. Ping, "Delay measurement time synchronization for wireless sensor networks," *Intel Research Berkeley Lab*, vol. 6, pp. 1–10, 2003.

[30] V. Cionca, T. Newe, and V. Dadârlat, "TDMA protocol requirements for wireless sensor networks," in *2nd Int. Conf. on Sensor Technologies and Applications*. IEEE, 2008, pp. 30–35.

[31] P. Manjunatha, A. Verma, and A. Srividya, "Multi-sensor data fusion in cluster based wireless sensor networks using fuzzy logic method," in *Third Int. Conf. on Industrial and Information Systems*, 2008, pp. 1–6.

[32] Z. Wen, R. Yang, P. Garraghan, T. Lin, J. Xu, and M. Rovatsos, "Fog orchestration for internet of things services," *IEEE Internet Computing*, vol. 21, no. 2, pp. 16–24, 2017.

[33] B. R. Sutherland, "Blockchain's first consensus implementation is unsustainable," *Joule*, vol. 3, no. 4, pp. 917–919, 2019.

[34] H. Kader and M. Hadhoud, "Performance evaluation of symmetric encryption algorithms," *Performance Evaluation*, pp. 58–64, 2009.

[35] M. A. Khan and K. Salah, "Iot security: Review, blockchain solutions, and open challenges," *Future generation computer systems*, vol. 82, pp. 395–411, 2018.

[36] J. H. Khor, M. Sidorov, M. T. Ong, and S. Y. Chua, "Public blockchain-based data integrity verification for low-power iot devices," *IEEE Internet of Things Journal*, 2023.

[37] W.-T. Tan and A. Zakhor, "Real-time internet video using error resilient scalable compression and tcp-friendly transport protocol," *IEEE Transactions on Multimedia*, vol. 1, no. 2, pp. 172–186, 1999.

[38] E. Sisinni, A. Saifullah, S. Han, U. Jennehag, and M. Gidlund, "Industrial internet of things: Challenges, opportunities, and directions," *IEEE transactions on industrial informatics*, vol. 14, no. 11, pp. 4724–4734, 2018.

[39] M. Zukerman, "Introduction to queueing theory and stochastic teletraffic models," *arXiv*, July 2013.

[40] C. Pop, M. Antal, T. Cioara, I. Anghel, D. Sera, I. Salomie, G. Raveduto, D. Ziu, V. Croce, and M. Bertoncini, "Blockchain-based scalable and tamper-evident solution for registering energy data," *Sensors*, vol. 19, no. 14, p. 3033, 2019.

[41] V. Manoharan, "Understanding the block propagation problem in blockchains," [Online] https://hackernoon.com/understanding-the-block-propagation-problem-in-blockchains-1t2s3x9b, August 2020.

[42] V. Rajendran, K. Obraczka, and J. J. Garcia-Luna-Aceves, "Energy-efficient collision-free medium access control for wireless sensor networks," in *Int Conf. on Embedded Networked Sensor Systems*, 2003, pp. 181–192.

[43] V. Buterin, "A next-generation smart contract and decentralized application platform - Ethereum White Paper," [Online] https://www.ethereum.org/pdfs/EthereumWhitePaper.pdf, 2014.

[44] Hyperledger, "An introduction to hyperledger," [Online] https://www.hyperledger.org/wp-content/uploads/2018/07/HL_Whitepaper_IntroductiontoHyperledger.pdf, 2018.

[45] "Whitepapers," [Online] https://www.avalabs.org/whitepapers, 2020.

[46] H. Malik, A. Manzoor, M. Ylianttila, and M. Liyanage, "Performance analysis of blockchain based smart grids with Ethereum and Hyperledger implementations," in *IEEE Int. Conf. on Advanced Networks and Telecommunications Systems*, 2019, pp. 1–5.

[47] "Bitinfocharts," [Online] https://bitinfocharts.com/mining-calculator.html.

[48] I. Coelho, V. Coelho, P. Lin, and E. Zhang, "Community yellow paper: A technical specification for neo blockchain," https://neoresearch.io/assets/yellowpaper/yellow˙paper.pdf, March 2019.

[49] C. Hoskinson, "Why we are building Cardano," [Online] url-https://whitepaper.io/coin/cardano, 2017.

[50] "EOS.IO technical white paper," [Online] https://eos.io/, June 2017.

[51] M. Hearn and R. G. Brown, "Corda: A distributed ledger," [Online] https://www.corda.net/wp-content/uploads/2019/08/corda-technical-whitepaper-August-29-2019.pdf, August 2019.

[52] "Binance whitepaper," [Online] https://www.binance.com/en, 2019.

[53] G. Wood, "Polkadot: vision for a heterogeneous multi-chain framework," [Online] https://whitepaper.io/document/596/polkadot-whitepaper, 2020.

[54] "White papers," [Online] https://algorand.com/technology/white-papers, 2019.

[55] A. Park and A. Veneris, "Conflux network: Engineering an economic design," [Online] https://whitepaper.io/document/717/conflux-network-whitepaper, 2021.

[56] N. Anita and M. Vijayalakshmi, "Blockchain security attack: A brief survey," in *10th IEEE Int. Conf. on Computing, Communication and Networking Technologies*, 2019, pp. 1–6.

[57] E. Georgiadis, "How many transactions per second can bitcoin really handle? theoretically," [Online] https://eprint.iacr.org/2019/416.pdf, 2019.

[58] J. Sedlmeir, H. U. Buhl, G. Fridgen, and R. Keller, "The energy consumption of blockchain technology: Beyond myth," *Business & Information Systems Engineering*, vol. 62, no. 6, pp. 599–608, 2020.

[59] "Distributed architectures: How fog and edge computing can fit into your cloud & colo strategy," [Online] https://www.digitalrealty.com/blog/fog-computing-and-what-it-means-for-the-cloud, September 2019.

[60] M. Zrikem, I. Hasnaoui, and R. Elassali, "Vehicle-to-blockchain (v2b) communication: Integrating blockchain into v2x and iot for next-generation transportation systems," *Electronics*, vol. 12, no. 16, p. 3377, 2023.

[61] Q. Zhou, H. Huang, Z. Zheng, and J. Bian, "Solutions to scalability of blockchain: A survey," *IEEE Access*, vol. 8, pp. 16 440–16 455, 2020.

[62] J. Chen and S. Micali, "Algorand: A secure and efficient distributed ledger," *Theoretical Computer Science*, vol. 777, pp. 155–183, 2019.

[63] C. Li, P. Li, D. Zhou, W. Xu, F. Long, and A. Yao, "Scaling nakamoto consensus to thousands of transactions per second," 2018.

[64] J. Alvarado and M. N. Halgamuge, "New era in the supply chain management with blockchain: A survey," in *Industry 4.0 and Hyper-Customized Smart Manufacturing Supply Chains*. IGI Global, Chapter 1, 2019, pp. 1–37.

[65] I. Jayatilleka and M. N. Halgamuge, *Internet of Things in healthcare: Smart devices, sensors, and systems related to diseases and health conditions*, ser. Real-Time Data Analytics for Large Scale IoT or Sensor Data. Elsevier, ISBN 9780128180143, 2020, vol. 6, ch. 15, pp. 1–59.

[66] J. Davis, "Pavo uses blockchain to increase farmers' yield," [Online] urlhttps://medium.com/coin-offerings/pavo-uses-blockchain-to-increase-farmers-yield-17c0e0a15df1, 2018.

[67] D. Schwartz, N. Youngs, and A. Britto, "The ripple protocol consensus algorithm," [Online] https://whitepaper.io/coin/ripple, 2011.

[68] A. Park and A. Veneris, "Conflux network: Engineering an economic design," [Online] https://confluxnetwork.org/files/Conflux_Economic_Paper_20201230.pdf, 2019.

Malka N. Halgamuge is a Senior Lecturer in Cybersecurity at RMIT University and the Chair of the IEEE Computational Intelligence Society, Victorian Section, Australia. From 2007-2021 Malka worked as a Researcher at the Department of Electrical and Electronic Engineering, The University of Melbourne. She obtained her PhD in the same department. She was awarded prestigious fellowships to work at University of California, Los Angeles, Lund University, Sweden, and the Chinese Academy of Sciences (CAS), Beijing, among others. Malka has been a chief investigator for multiple grants totaling over $1 million. She is passionate about research in IoTs, Data Communications, Cyber Security, Blockchain, Machine & Deep Learning.

Geetha K. Munasinghe is a Verification & Validation Engineer at Sine Group Pty Ltd., Adelaide, Australia. She received her B.Sc. degree in Information and Communication Technology from Colombo University, Sri Lanka, in 2010 and a master's degree in Information Technology from Charles Sturt University, Australia, in 2020. Her current research interests include blockchain technology, the Internet of Things, and data security.

Moshe Zukerman received a B.Sc. degree in industrial engineering and management, an M.Sc. degree in operations research from the Technion – Israel Institute of Technology, Haifa, Israel, and a Ph.D. degree in engineering from the University of California, Los Angeles, in 1985. He was an independent consultant with the IRI Corporation and a Postdoctoral Fellow with the University of California, Los Angeles, during 1985–1986. During 1986–1997, he was with Telstra Research Laboratories (TRL), first as a Research Engineer and, during 1988—1997, as a Project Leader. He also taught and supervised graduate students at Monash University during 1990–2001. During 1997–2008, he was with The University of Melbourne, Victoria, Australia. In 2008 he joined the City University of Hong Kong as a Chair Professor of Information Engineering, and a team leader. From December 2020 to September 2022, he also serves as the Acting Chief Information Officer of CityU. He has over 300 publications in scientific journals and conference proceedings. He has served on various editorial boards such as Computer Networks, the IEEE Communications Magazine, the IEEE Journal of Selected Areas in Communications, the IEEE/ACM Transactions on Networking, and Computer Communications.