Block Hunter: Federated Learning for Cyber Threat Hunting in Blockchain-Based IIoT Networks

Abbas Yazdinejad, Ali Dehghantanha, Senior Member, IEEE, Reza M. Parizi, Senior Member, IEEE, Mohammad Hammoudeh, Senior Member, IEEE, Hadis Karimipour, Senior Member, IEEE, and Gautam Srivastava, Senior Member, IEEE

Abstract—Nowadays, blockchain-based technologies are being developed in various industries to improve data security. In the context of the Industrial Internet of Things (IIoT), a chain-based network is one of the most notable applications of blockchain technology. IIoT devices have become increasingly prevalent in our digital world, especially in support of developing smart factories. Although blockchain is a powerful tool, it is vulnerable to cyberattacks. Detecting anomalies in blockchain-based IIoT networks in smart factories is crucial in protecting networks and systems from unexpected attacks. In this article, we use federated learning to build a threat hunting framework called block hunter to automatically hunt for attacks in blockchain-based IIoT networks. Block hunter utilizes a cluster-based architecture for anomaly detection combined with several machine learning models in a federated environment. To the best of our knowledge, block hunter is the first federated threat hunting model in IIoT networks that identifies anomalous behavior while preserving privacy. Our results prove the efficiency of the block hunter in detecting anomalous activities with high accuracy and minimum required bandwidth.

Index Terms—Anomaly detection, blockchain, federated learning (FL), industrial Internet of Things (IIoT), Internet of Thing (IoT), threat hunting.

I. INTRODUCTION

The technological trajectory of blockchain makes it a valuable tool in many areas, including healthcare, military, finance, and networking, via its immutable and tamper-proof data security advantages. With the ever-increasing use of Industrial Internet of Things (IIoT) devices, the world is inevitably becoming a smarter interconnected environment; especially factories are becoming more intelligent and efficient as technology advances [1]. IIoT is considered a subcategory of the Internet of Things (IoT). There are, however, differences between IoT and IIoT in terms of security requirements. While the IoT makes consumers’ lives easier and more convenient, the IIoT aims to increase production safety and efficiency. IIoT devices are mainly used in business-to-business (B2B) settings, while IoT devices are mostly considered in business-to-consumer (B2C) environments. This would lead to a different threat profile for IIoT networks compared to their IoT counterparts where device-to-device transactions are of utmost importance.

IIoT networks provide an umbrella for supporting many applications and arm us to respond to users’ needs, especially in an industry setting such as smart factories [1]. Blockchain technology advantages lead to its wide adoption in IIoT-based networks such as smart factories, smart homes/buildings, smart farms, smart cities, connected drones, and healthcare systems [1], [2]. While the focus of this article is on the security of blockchain-based IIoT networks in smart factories [3], [4], the suggested framework may be used in other IIoT settings as well.

In modern smart factories, many devices are connected to the public networks, and many activities are supported by smart systems such as temperature monitoring systems, Internet-enabled lights, IP cameras, and IP phones. These devices are storing private and sensitive data and may offer safety-critical services [1], [3]. As the number of IIoT devices in smart factories increases, the main issue will be storing, collecting, and sharing data securely. Industrial, critical, and personal data are, therefore, at risk in such a situation. Blockchain technology can ensure data integrity inside and outside of smart factories through strong authentication and ensure the availability of communication backbones. Despite this, privacy and security issues are significant challenges in IIoT [3], [4]. The probability of fraudulent activity occurring in blockchain-based networks [2],

Manuscript received 20 December 2021; revised 8 March 2022; accepted 12 April 2022. Date of publication 19 April 2022; date of current version 9 September 2022. Paper no. TII-21-5631. (Corresponding author: Ali Dehghantanha.)

Abbas Yazdinejad and Ali Dehghantanha are with the Cyber Science Lab, University of Guelph, Guelph, ON N1G 2W1, Canada (e-mail: ayszadine@uoguelph.ca; adehghan@uoguelph.ca).

Reza M. Parizi is with the College of Computing and Software Engineering, Kennesaw State University, Marietta, GA 30060 USA (e-mail: rparizi1@kennesaw.edu).

Mohammad Hammoudeh is with the Department of Information and Computer Science, King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia (e-mail: m.hammoudeh@kfupm.edu.sa).

Hadis Karimipour is with the School of Engineering, Department of Electrical and Software Engineering, University of Calgary, Calgary, AB T2N 1N4, Canada (e-mail: hadis.karimipour@ucalgary.ca).

Gautam Srivastava is with the Department of Math and Computer Science, Brandon University, Brandon, MB R7A 6A9, Canada, and also with the Research Centre for Interneural Computing, China Medical University, Taichung 404, Taiwan (e-mail: srivastavag@brandou.ca).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TII.2022.3168011.

Digital Object Identifier 10.1109/TII.2022.3168011

1551-3203 © 2022 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See https://www.ieee.org/publications/rights/index.html for more information.
[4] is an important issue. Even though blockchain technology is a powerful tool, it is not protected from cyberattacks either. For example, a 51% cyberattack [2] on Ethereum Classic (ETC), and three consecutive attacks in August of 2020 [5], which resulted in the theft of over $5 M worth of cryptocurrency, have exposed the vulnerabilities of this blockchain network.

Smart factories should protect users’ data privacy during transmission, usage, and storage [4]. Stored data are vulnerable to tampering by fraudsters seeking to access, alter or use the data with malicious motives. Statistically speaking, these attacks can be viewed as anomalous events, exhibiting a strong deviation from usual behavior [2], [6]. Detecting out-of-norm events are essential for threat hunting programs and protecting systems from unauthorized access by automatically identifying and filtering anomalous activities. [6], [7].

The main objective of this article is to detect suspicious users and transactions in a blockchain-based IIoT network specifically for smart factories. Here, abnormal behavior serves as a proxy for suspicious behavior as well [4]. By identifying outliers and patterns, we can leverage machine learning (ML) algorithms to identify out-of-norm patterns to detect attacks and anomalies on blockchain. Because deep neural networks learn representations automatically from data that they are trained on, they are the candidate solution for detecting anomalies [4], [7]. However, there are challenges with any ML and deep learning-based anomaly detection techniques. These methods suffer from training data scarcity problems, and privacy issues [7].

Detecting anomalies in the blockchain is a complicated issue [8]. Not only each block needs to be sent to a central server, which increases the training time, but also the model requires new block data in the testing phase [8]. In addition, when ML models are frequently updated to respond to new threats and detect anomalies, malicious adversaries can launch causative/data poisoning attacks to degrade the ML model deliberately. Attackers may intentionally send crafted payloads to evade anomaly detection.

A novel and practical approach would be to employ federated learning (FL) models to detect anomalies while preserving data privacy, and monitoring data quality [7], [9]. FL allows edge devices to collaborate during the training stage while all data stays on the device. We can train the model on the device itself instead of sending the data to another place, and only the updates of the model are shared across the network.

FL has become a trend in ML where smart edge devices can simultaneously develop a mutual prediction between each other [7], [10]. In addition, FL ensures multiple actors construct robust ML models without sharing data, addressing fundamental privacy, data security, and digital rights management challenges. Considering these characteristics, this article uses an FL-based anomaly detection framework called Block Hunter capable of detecting attack payloads in blockchain-based IIoT networks.

The main contributions of this article are summarized as follows.

1) Utilize a cluster-based architecture to formulate an anomaly detection problem in blockchain-based smart factories. The cluster-based approach increases the hunting efficiency in terms of bandwidth reduction and throughput in IIoT networks.

2) Apply a federated design model to detect anomalous behavior in IIoT devices related to blockchain-based smart factories. This provides a privacy-preserving feature when using ML models in a federated framework.

3) Implementation of various anomaly detection algorithms such as clustering-based, statistical, subspace-based, classifier-based, and tree-based for efficient anomaly detection in smart factories.

4) The impact of block generation, block size, and miners on the Block Hunter framework are considered. Moreover, the performance measurements like Accuracy, Precision, Recall, F1-score, and True Positive Rate anomaly detection are discussed.

The rest of this article is organized as follows. Section II discusses anomaly detection works in the blockchain and FL. Section III describes the Block Hunter framework and presents the network model and topology design. In Section IV, methodology and ML approaches to identify anomalies are discussed. In Section V, we present the assessment of the Block Hunter framework. Finally, Section VI concludes this article.

II. RELATED WORK

In the face of increasing cybersecurity threats and enlarging attack surfaces, it is becoming more complex and challenging to secure IIoT networks and environments [11], [12]. Furthermore, as blockchain technology is increasingly applied in a broad range of fields, anomaly detection is becoming more and more important. Anomalies can thus occur in a wide range of blockchain-based applications. This section discusses research relating to anomaly detection, especially in relation to blockchain and FL.

In [13], the authors proposed a framework as blockchain anomaly detection (BAD) to detect anomalies in blockchain-based systems. BAD collects potential malicious activities using blockchain metadata and has interesting features like distribution to avoid the central point of failure, trust, and privacy. Another work, [14], suggests blockchain and anomaly detection systems that recognize frauds when IoT meter data are tampered with. This research uses polynomial regression, density-based spatial clustering of applications with noise (DBSCAN), autoencoder, and long short-term memory (LSTM) methods to detect tampering.

Sayadi et al. [15] propose an algorithm for anomaly detection over bitcoin electronic transactions. They examined the one-class support vector machines and the K-means algorithms to group outliers similar in both statistical significance and type. They analyzed their work by generating detection results and found that we could obtain high-performing results on accuracy. In [16], the authors suggested an approach based on the semantics of anomalies in blockchain-based IoT networks. A method was presented to detect anomalous behavior in blockchain that gathers metadata in forks to determine mutual informational recognition of anomalous activity. They developed a tool that improves blockchain security and connected devices. Also, in [17],
has introduced encoder–decoder deep learning regression for detecting the blockchain security. This work developed an anomaly detection framework that relies on aggregate information derived from bitcoin blockchain monitoring. Their experiments have demonstrated that their model can detect publicly reported attacks using the historical logs of the Ethereum network.

Investigation in blockchain shows blockchain Edge of Things (BEoT) can enable future services and applications, according to [18]. The authors discuss the latest developments and applications of BEoT. Their findings show that blockchain technology has grown inquisitive beyond cryptocurrency in the Edge of Things (EoT) as it provides decentralization, immutability, and traceability in EoT systems.

In [7], the authors provided an FL approach to anomaly detection for smart buildings that made use of an additional recurrent neural network for a privacy-by-design approach. It shows that it is more than twice as fast during training as its centralized counterpart. They were able to achieve superior performance in both classification and regression responsibilities compared to baseline methods. Also, in [19], Nguyen et al. presented a self-learning federated system for detecting anomalies in IoT networks. Their system is based on device communication profiles that can detect adverse changes in IoT devices’ communication. It employs FL for efficiently aggregating behavior profiles. It was one of the first systems to employ this approach to anomaly detection. Since this system can handle emerging new threats, it can be used to handle a wide variety of threats.

The authors in [20] put forward an approach via FL for detecting abnormal client behavior. The ability to detect anomalous client behavior at the server level is mentioned in their article. They detected abnormalities across networks using low-dimensional surrogates of model weight vectors. Experimentally, the detection-based method significantly outperforms the conventional methods based on defense. Furthermore, there is a work [21] involving the use of Deep Learning and blockchain-based FL to detect COVID-19. They develop a framework to gather data from various sources and generate a global deep learning model using blockchain-based federated training. By using blockchain to authenticate the data, FL enables models to be trained while preserving privacy. By combining blockchain with federated e-learning, they developed a system for training global models collaboratively. Their results show better performance in detecting patients via this method.

Chai et al. [22] proposed a hierarchical blockchain framework and FL to learn and share environmental data. This framework is functional and efficient for large-scale vehicular networks. FL-based learning meets the Internet of vehicles’ distributed pattern and privacy requirements. Sharing behavior is modeled as a multileader, multiplayer trading market process to stimulate knowledge sharing. Simulated results indicate that an algorithm based on hierarchical structures can enhance sharing, learning, and managing specific malicious attacks. Furthermore, the authors in [23] deliver a comprehensive investigation on how FL could supply better cybersecurity and prevent various cyberattacks in real time. This work highlights some main challenges and future directions on which the researchers can focus for adopting FL in real-time scenarios.

III. PROPOSED BLOCK HUNTER FRAMEWORK IN BLOCKCHAIN-BASED IIOT NETWORKS

Fig. 1 presents a detailed overview of the proposed blockchain-based IIoT network for smart factory applications. This cluster-based architecture combines users, base stations, WiFi, service providers, and smart factories connected to the blockchain network. Smart factories include several smart-connected devices. The service provider can collect sensor data in smart factories and use them based on their applications and services. In addition, Fig. 1 illustrates the relationship between the peers in terms of information between the factory and its smart devices. A transaction represents the exchange of sensitive factory information between parties during working in the blockchain network. There are several inputs and outputs in a transaction. Blocks consist of a list of transactions, a reference to the previous block, and a hash. Every block is made up of transactions that the block creator, referred to as the miner, has accepted into its memory pool from the previous block. Considering rigid industrial standards that should be followed when designing and implementing smart factories, it is practical to assume that the functionality of smart factories in each cluster is the same.

Detecting anomalous activities is a significant contributor to automatically protecting a system from unexpected attacks. Anomalies in blockchain must be detected by sending each block of data to a central server for each block update. This is not efficient and also imposes privacy concerns. FL solutions are promising in tackling this issue. We use FL to update the model frequently and to obtain a global model for detecting an anomaly. After learning about each smart factory’s data, devices, and service provider, the model’s parameters will be sent to
the parameter server for aggregation and to update our general model. We provide the details of implementing the Block Hunter framework in the following subsections.

### A. Role of FL to Detect Anomalies in Block Hunter

We distribute local models across the blockchain-based IIoT network instead of learning an anomaly detection model and evaluating it on a single node. As shown in Fig. 2, the FL setup involves local models as well as distributed smart factories nodes. Instead of a centralized learning environment, setup involves local models as well as distributed smart factories evaluating it on a single node. As shown in Fig. 2, the FL network instead of learning an anomaly detection model and a factor of the batch size for the global operation;

![Fig. 2. Proposed federated anomaly detection in the Block Hunter framework.](image)

Algorithm 1: Federated Anomaly Detection Model.

1. **Input:** Pre-trained model
2. **Output:** Global anomaly-detection model
3. **Initializing:** $(t = 0)$ // start to set values
4. Parameter server update $(W)$
5. Define initial values $= B, E, h, C, K$
6. initial local models $(w)$
7. Model $(m_i) = \text{set parameters} (w_1, \ldots, w_n)$
8. Client model update
9. Local models $\rightarrow$ smart factories' clusters
10. **Federated Training:** // beginning FL method
11. While $(K > 0)$
12. Get (local models)
13. For local epoch $E$
14. For each batch 1 to $b$
15. Run local models
16. Obtain and set model parameters
17. Return (Model parameters)
18. Parameter server $= \text{FedAvg} (w)$
19. **Update** $(w, m)$
20. Decrypted $(w, m)$
21. $D =$ split Data into batches of size $B$
22. for local epoch $E$ from 1 to $B$
23. for batch $x < B$
24. return $w$ and $D$ to server
25. Return updated Model
26. **FedAvg:** // model aggregation
27. Server (Initialize $w_0$
28. encryption (Homomorphic)
29. $P =$ compute loss $(w, b)$
30. for round $c = 1$ to $k$
31. Server: Send $w_{i-1}$ to Smart factory $i - 1$
32. $E = E + 1$
33. Parameter server $= \text{Update} (w_{k-1}, \ldots, w_k)$

1) **Federation construction:** The subset of smart factory members, cluster, is selected to receive the model locally.
2) **Decentralized training:** When a cluster of smart factories is selected, it updates its model using its local data.
3) **Model accumulation:** Responsible for accumulating and merging the data models. Data are not sent and integrated from the federation to the server individually.
4) **Model aggregation (FedAvg):** Parameter server aggregates model weights to compute an enhanced global model.

At runtime, pretrained models as local models are sent to clusters in the Block Hunter framework from the Parameter Server, considering blockchain-based IIoT networks environments. The local models are sent to smart factories for training based on local epochs. Then, the parameters and hyperparameters will be forwarded to the Parameter Server for aggregating model weights to compute the global model. The global model is an ML model that holds in the Parameter Server to update its parameters. When a new cluster joins our framework, the latest global model will be sent to that cluster as a pretrain model.
so that in the real-world application, we can simply follow this approach. The updated global model is sent to clusters gradually during evolution.

B. Anomaly Detection in Blockchain-Based IIoT Network

Smart factories have sensitive data, so storing it on the blockchain with its limited storage is both financially and computationally costly. Therefore, the actual smart device and sensor data are stored in the smart factory. The smart factory data include information about the type of data and control states as well.

The premise behind the development of an anomaly detection framework for the blockchain-based IIoT networks in smart factories lies in providing a new decentralized system based on FL that leverages all smart factory data while protecting their privacy. In addition, we will reach a point where we need to attend to the issue of a fork in the blockchain scope during anomaly detection. In some instances, devices or nodes do not agree on the state of the blockchain, leading to the fork issue in the blockchain. When blockchain-based applications are being developed, forks become more concerned because they have the potential to be used for malicious purposes. Indeed, a global ML model can use all of the collected information from previous forks to detect anomalies during training. This approach has the advantage that while attacks may only happen once within a smart factory, they behave the same way when repeated against other smart factories over time. Hence, information on past attacks may help us blacklist them and prevent them from occurring in the future. The advantage of FL is clear since it will train the global ML model for anomaly detection.

Based on Fig. 1, each participant in a smart factory can provide a fake blockchain transaction as a side channel to deliver a message. A malicious transaction as well as creating a fake block are also possible in this situation. A malicious transaction is a special type of fake transaction, which consists of a hidden message that is aimed at disrupting the network by hitting a specific peer. Inserting fake blocks are blockchain blocks that contain one or more stolen/malicious transactions. Fake blocks can either be eventually discarded or accepted into the mainstream chain.

Our solution considers smart factories’ data and chain forks. We collect, enrich, and share such information with other local ML models across the network. We used the specific information for training anomaly detection in each local ML model that contains sensitive smart factory data, the features of previous forks, and the number and type of malicious transactions that occurred. As a result, we can hunt an anomaly by the Block Hunter in a blockchain-based IIoT network for smart factories.

To protect the privacy of the data, we only share the parameters of pretrained models instead of the original data from smart factories and their blockchain. This work aims to train a global anomalous detection model through locally trained subprotocol models based on the Block Hunter framework.

Regarding the threat model, the solution proposed in this article has been designed to be resilient against any class of attacks where a malicious entity can append to the blockchain system.

C. Network Model and Topology Design

This section discusses the efficient network model and topology design for blockchain-based IIoT networks. Wireless sensor networks have a variety of topologies, which affect their performance and behavior. Some of the metrics include throughput, reliability, energy consumption, and latency [26]. Therefore, we propose blockchain technology’s cluster-based formation model for smart factories. Cluster-based architecture provides more efficient use of resources [27] and throughput during the blockchain run in each smart factory. Clustering reduces the computational complexity in the creation of the underlying network through a hierarchical approach [26]. It is especially so with blockchain-based IIoT networks that are expected to encompass large numbers of individual devices. Also, we believe that cluster-based architecture will enable us to hunt and manage anomalies better in each smart factory zone and increase the network’s throughput.

In each cluster, the smart factory controls all IIoT devices’ activities, and one of the smart factories is usually known as cluster head (CH) or a leader node. A CH can perform extra duties in blockchain-based networks like taking part in the mining process by reviewing aspects such as energy, memory, and computing power. Fig. 1 shows the clustering strategy in the blockchain-based smart factory network model.

Based on the target Block Hunter framework, which can be represented as a directed graph \( G = (S, D) \) with \( D \) being the set of IIoT devices, representing smart devices, \( D = \{d_1, d_2, \ldots, d_n\} \), and \( S = \{s_1, s_2, \ldots, s_n\} \) is the set of smart factories in each cluster. In \( S_{1} = [t_1, t_2, \ldots, t_m] \), we consider the set of transactions in smart factory \( S_{1} \) that belongs to the blockchain network. \( B = [b_1, b_2, \ldots, b_3] \) represents the number of existing blocks in the blockchain network. More formally, \( s_n = \bigcup_k s_j \times D_{kj} \), with \( k \) being the number of deployed clusters, and \( j \) is smart factories in that cluster. It should be noted that the set of IoT devices refer to a smart factory, \( D_{kj} \in [1, j] \) in the \( K \)th cluster.

It is possible to summarize the distribution of smart factories with their devices in the Block Hunter, the proposed cluster-based architecture, in (1), distance function, \( Df \). This is the point at which smart factories and IoT devices will cluster based on most centrality derived from a distance measure based on the presence or absence of shared neighboring devices in the space of \((i, j)\).

\[
D_f(D_{ki}, D_{kj}) = \sqrt{\sum_{i, j=1}^{K} (S_{nj} - S_{ni})^2 \times (D_{kj} - D_{ki})^2}. \tag{1}
\]

The clustering part is shown in Algorithm 2, and it can be considered a piece of the overall algorithm in the Block Hunter. Algorithm 2 collects the locations of smart factories and their IoT devices. Based on (1), we measure each smart factories’ distance and their devices and record it until we obtain the cluster-based architecture. Afterward, the cluster calculates a collection of \( S \) nearest smart factories for each IoT device, \( D \).

Setting model parameters in the parameter server and sending pretrained models to clusters happen during initializing. Next,
Algorithm 2: Cluster Formation Strategy in Block Hunter.

1: **Input:**
2:   Get = (S, D)
3: **Initialize:**
4:   Define initial values
5:   Set Number of Cluster = K
6:   Get loc = S = \{s_1, s_2, \ldots, s_n\} // location of smart factories
7:   Get loc = D = \{d_1, d_2, \ldots, d_n\} // location of devices
8:   s_n = \bigcup_{j}^{K} s_j \times D_{kj} // Deployed clusters and smart factories
9: **Main():**
10:   Get (K, S, D)
11:   While (K > 0)
12:   
13:     For z each K
14:     \textbf{Compt} = D_{fz}
15:     (D_{ki}, D_{kj}) = \sqrt{\sum_{i, j=1}^{K} (S_{nj} - S_{ni})^2 \times (D_{kj} - D_{ki})^2} // Calculating distance for finding neighboring devices. The presence or absence of devices in the space of (i, j)
16:     Set_area = K_z
17:     Client distance update
18:     Marge neighbor
19:   }
20:   Return K

In this section, we study several ML techniques for identifying and detecting anomalies in the Block Hunter framework.

A. Neural Encoder–Decoder (NED) Model

An example of a classifier-based anomaly detection algorithm is the NED model. The proposed anomaly detection framework develops an NED model that summarizes the information about the blockchain’s status and transactions, and then, rebuilds the initial data from this space. Encoding/decoding preserves the data’s basic properties when the current status is consistent. Differently, anomalous situations exhibit inconsistent values, ultimately leading to a failing reconstruction. In an encoder–decoder, this quantity would be paraphrased as noise, and therefore, would be failing when reconstructing. Therefore, the difference between the initial and reconstructed values would highlight the anomalous and abnormal situation, thereby triggering an alert [8], [28]. NED models analyze sequences of temporally sorted events. In general, we suppose that the data will be sequenced as \( P = \{P_1, P_2, \ldots, P_n\} \) concerning some period of observation, where \( P_t \) is an assessment of the properties of the \( t \)th event in the chronological order of events in \( P \). Anomalous events occur in \( P \), i.e., a vector \( P_t \) drastically differs from its neighbors \( P_t \).

B. Isolation Forest (IF)

The Isolation Forest (IF) model falls under the Tree-based anomaly detection algorithms category. The approach has gained much universal acceptance in recent years because it is unsupervised. IF is a concept based on the idea that it is more prudent to isolate data anomalies rather than generalize the norms. It is a recursive and random partitioning process to isolate the anomalous data point in the dataset until it simply describes the stored data. A tree structure represents the recursive partition. A forest of isolation trees is the foundation of the IF algorithm, where cells in the dataset are randomly selected from the data to form a forest of normal and outlier cells. These trees are binary trees that have zero or two child nodes, and an IF contains isolation trees of this type [8], [29]. Consider that \( X \) is either a leaf node that does not have any children or a parent node that has two children named \( XL \) and \( XR \). To choose which child nodes belong to which parents, a test must be attached to node \( X \). The testing procedure involves selecting a random feature \( f \) across all the data points and an arbitrary splitting point \( q \). Node \( f < q \) is in the zone of \( XL \), and \( f \geq q \) is in the zone of \( XR \).

C. Cluster-Based Local Outlier Factor (CBLOF)

Our CBLOF model belongs to the classifier-based algorithm-based anomaly detection category. Our CBLOF model belongs to the classifier-based algorithm-based anomaly detection category. Within this algorithm’s anomaly detection methodology, the data are clustered into clusters, based on which anomaly scores can be computed similar to those of the local outlier factor algorithm and so on. This algorithm’s underlying principle of anomaly detection is based on clustering datasets together. This algorithm creates clusters using groups in a dataset by arbitrary clustering algorithms that assign a specific observation to a cluster. The clusters are sorted in each case corresponding to their respective sizes of \( |F_1| > |F_2| > \ldots > |F_k| \) where \( F_1, F_2, \ldots, F_k \) all represent the cluster for which number \( k \) is the cluster number [8]. A pair of clusters, when intersecting with each other, should give rise to an empty set. However, all these clusters’ unions should represent all of the observations in dataset \( D \); we are supposed to search for a boundary index value that separates the small clusters from the large clusters. Finally, we calculate the CBLOF scores for each observation by using the following equation, \( 1 \leq i \leq k \):

\[
CBLOF(t) = \begin{cases} 
|F_k|.\text{dis}(t, F_i) & t \in F_i \\
|F_k|.\text{min}(\text{dist}(t, F_i)) & t \in F_i.
\end{cases}
\]

D. Principal Component Analysis (PCA)

A PCA model is a subsequence-based anomaly detection algorithm. PCA is commonly considered a method to reduce the dimensionality algorithm. The variance-covariance of dataset characteristics can be used to construct new variables known as principal components, which are functions of original variables. For PCA, one uses \( p \) distinct linear combinations of random variables \( x_1, x_2, \ldots, x_p \). The principal component has the
following characteristics: they are uncorrelated to each other. Each component’s variance decreases in descending order, with the principal component containing the highest variance and the subsequent details having lower variances. When combining all the principal components’ variations, the sum of the total variation of the original features is always equal to the total variation of all the principal components. To estimate the principal components of a system, we can use eigenanalysis to get the correlation matrix, or covariance matrix of data features \[8\], \[30\].

The PCA algorithm detects anomalies by getting rid of any outliers. The outliers are determined by the Mahalanobis distance that is carried out repeatedly to eliminate all data points with high Mahalanobis distance values. Where \( S \) is a covariance matrix, \( x_i \) is the measure of an observation of the \( i \)th feature in data, and \( x \) is the mean of all observations, Mahalanobis distance is denoted as follows:

\[
D = \sqrt{(x_i - \bar{x})^T S^{-1} (x_i - \bar{x})}.  \tag{3}
\]

E. \( K \)-means

In the cluster-based detection algorithms category, \( K \)-means is a clustering-based algorithm. As one of the most popular clustering algorithms, \( K \)-means is also commonly used as an anomaly detection algorithm. It has been introduced as an unsupervised learning scheme. The data are divided into \( k \) different clusters, with each sample belonging to the cluster with the closest mean value within each cluster. Across clusters, there is a cluster centroid \( c_i \), which is the mean of observations from each cluster in that cluster. When assessing the similarities among independent observations, the similarity measure employed is Euclidean distance, where \( x_i \) is the measurements and \( c_i \) is the centroids, and \( n \) outlines the number of independent measurements \[8\], \[31\].

\[
d^2(X, c) = \sum_{i=1}^{k} (X_i - c_i)^2. \tag{4}
\]

V. DISCUSSION AND EVALUATION

This section evaluates the performance of the Block Hunter and provides results and discussion.

A. Experimental Setup

We performed an experimental setup on Intel(R) Core(TM) i7-10700KF CPU at 3.80 GHz 3.79-GHz, Linux 64-bit operating system (Ubuntu 20.04), and equipped it with 16-GB DDR4 memory. To evaluate our network model and cluster-based topology design in the proposed framework, we apply the Bitcoin Simulator.\(^1\) The Bitcoin Simulator is an open-source bitcoin simulator developed on NS3. The Bitcoin Simulator has been tested with NS3. Also, we consider LENA as an NS-3 module to simulate 3GPP networks. The NR module is a pluggable module for NS-3 that can be used to simulate New Radio (NR) cellular networks. NS-3 supports the widest variety of network models and protocols and supports the greatest variety of networking devices. Indeed, wireless networks and protocols rely on the NS-3 to determine their performance. Therefore, the assessment of the proposed federated framework will do on the performance metrics such as the impact of block size, number of blocks, number of IoT devices, and number of miners. The implementation details of the Block Hunter framework is presented in Table I.

For the federated setup, we have considered PySyft\(^2\) and PyTorch.\(^3\) PySyft is an open-source library that allows us to create VirtualWorkers for training our ML models to detect an anomaly. It is designed to allow users to create a private and secure ML model, and it is built into some existing ML libraries, such as PyTorch. Our framework is trained with the FedAvg method with \( E = 4 \) local epoch and fraction \( c = 6e - 3 \). \( E \) mentions to Local batch size used at each learning iteration, and \( c \) refers to the number of smart factories used at each iteration. It is also important to emphasize \( e \). The \( e \) is denoted exp, which is short for exponential. Finally, an SGD optimizer is used for training the models with a learning rate of \( 3e - 2 \).

\[\text{Table I} \]

FEDERATED FRAMEWORK PARAMETERS

| Parameter          | Description                  |
|--------------------|------------------------------|
| Simulator          | Bitcoin simulator/NS3/NS3+ENA|
| Operating system   | Ubuntu 20.04                 |
| CPU                | i7-10700KF                    |
| RAM                | 16-GB DDR4                   |
| Number of clusters | 50                           |
| Number of mining   | 3                            |
| Clients            | 100                          |
| Total epoch        | 4                            |
| Fraction of smart   | 0.6                          |
| Inference model    | Random forest model           |
| Traffic Type       | Contact Lo Rate               |
| Number of IoT      | 200                          |
| Datasets           |                              |
| Ethereum           |                              |

B. Datasets

The proposed framework is evaluated by two datasets on the blockchain side, providing conditions for blockchain adoption in smart manufacturing systems, and also two IIoT-related datasets for assessing BlockHunter for smart factories. The Bitcoin Transaction Dataset (BTD)\(^4\) designed for research on blockchain anomaly and fraud detection. It has been donated to the IEEE data port online community for academic exploration. Because the dataset is imbalanced and contains roughly 30 million transactions, it presents a challenge in creating an anomaly detection model that captures all of them. The dataset is an implementation of a research project that presents anomaly detection within the context of blockchain technology and its applications in the monetary domain. It extracts blockchain data and uses ML techniques to hunt potentially malicious transactions.

Another dataset is ETC\(^5\) that is a BigQuery Dataset. We will be able to access ETC transactions and block history in this dataset. The ETC open-source, based on the Ethereum platform, is a

\[1\] [Online]. Available: https://github.com/c3ht3ng/Bitcoin-Simulator-NS3

\[2\] [Online]. Available: https://github.com/OpenMined/PySyft

\[3\] [Online]. Available: https://pytorch.org

\[4\] [Online]. Available: https://ieeexplore.ieee.org/document/8785320

\[5\] [Online]. Available: https://www.kaggle.com/bigquery/crypto-ethereum-classic
platform that enables distributed computing by using a public, distributed decentralized network for executing scripts with the ability to manage smart contracts. The dataset consists of all blocks, contracts, logs, tokens, traces, and transactions contained within the blockchain network.

In choosing IIoT-related datasets, two well-known datasets have been considered: Gas Pipeline (GP) and Secure Water Treatment (SWaT). They are well fit for the IIoT environments and are publicly available [32], [33].

C. Experimental Analysis

A cluster-based architecture provides more efficient use of resources and throughput during the blockchain run in smart factory applications. To evaluate the performance of the Block Hunter, cluster-based architecture, the simulation parameters are presented in Table I. To accomplish more realistic results, we did the simulation 20 times and designed another scenario as a noncluster model to compare the architectural models’ performance during the simulation. The noncluster model combined blockchain technology with the standard network model and did not consider and divide it into cluster architecture. It has no features and typologies of cluster-based architecture such as adjacencies with other clusters or part of the network, flexibility, and scalability during run time. Conversely, in cluster-based architecture, each cluster has adjacencies with other clusters and supports the dynamic characteristics of a network. In the following, we address the impact of Block generation, the impact of the Block size, and the impact of the number of miners in the evaluation. In the proposed framework, the public blockchain network is deployed among clusters that include smart factories. We need a public blockchain to allow any smart factories to join and keep the system completely decentralized. Additionally, public blockchains give all participants equal access to the chain.

1) Impact of the Block Generation: Block generation interval is regarded as an important metric for measuring the performance of blockchain networks. If we have an organized topology and structure, the block generation will be more efficient to support nodes than in a distributed network with a solid and organized structure. Further, since blocks are generated more frequently in individual clusters instead of generated in batches that consume a considerable amount of bandwidth, we can better manage and use the bandwidth. Fig. 3(a) shows the bandwidth efficiency of the cluster-based design (proposed architecture) compared to the noncluster-based design.

Although there is an increase in block generation time in the noncluster-based design, more blocks will be generated in the network and consume more bandwidth. Hence, cluster-based architecture provides a better performance since the nodes are distributed across the whole network (currently, there are 5000 reachable nodes in \( K = 50 \) Clusters).

2) Impact of the Block size: Block size has a significant impact on the performance of blockchain. The block size determines the highest number of transactions that can be approved within a block. This size, thus, controls the throughput (transactions/second) obtained by the proposed design. Larger blocks cause more sluggish propagation in each cluster than smaller blocks. Fig. 3(b) and (c) shows that the bandwidth consumption and throughput increase with the increasing block size from 0.5 to 8 MB. This directly impacts both the bandwidth and throughput of the proposed model. As expected, Block Hunter has a higher performance because of better network communication, efficient topology management, and minimized delay.
3) Impact of Number of Miners: The number of miners in a given architecture directly impacts throughput (transactions/second). According to Fig. 3(d), an increasing number of miners from 16 to 256 and the block size to 1 MB in all clusters increased the model throughput. The increase in the number of miners makes it easier for smart factories to reach a consensus. Additionally, the proposed cluster-based architecture can handle more transactions in each block by increasing the block size. Consequently, it will grow the proposed architecture’s throughput rate and offer a better performance.

4) Nomaly Detection Rate: This subsection aims to assess some well-known ML models such as $K$-means, PCA, CBLOF, IF, and NED to hunt anomalies in the Block Hunter framework. We evaluate these models by comparing their average performance, such as Accuracy, Precision, Recall, and F1-score as follows. These include,

\[
\text{Accuracy (Acc)} = \frac{TP + TN}{TP + TN + FN + FP},
\]

\[
\text{Recall (Rec)} = \frac{TP}{TP + FP}, \quad \text{Precision (Pre)} = \frac{TP}{TP + FP}
\]

and

\[
\text{F1-score (F1)} = \frac{2 \times \text{Precision (Pre)} \times \text{Recall (Rec)}}{\text{Precision (Pre)} + \text{Recall (Rec)}}.
\]

Tables II and III display the measured performance of the Block Hunter during applying ML models, $K$-means, PCA, CBLOF, IF, and NED in terms of Precision, Accuracy, F1-score, and Recall based on BTD and ETC Blockchain datasets. To minimize the loss function, all hyperparameters are maximized.

In Tables II and III, we can see that NED and IF have the highest accuracy during the anomaly detection while their accuracy is almost similar. In addition, we reported the area under the curve (AUC) of receiver operating characteristic (ROC) as shown in Fig. 4(a)–(e). The ROC curves for CBLOF, $K$-means, PCA, IF, and NED are presented in a federated setting. By examining the visuals and using the highest level of accuracy metric, the AUC for ROC curves show a comparable ROC curve for all algorithms. The AUC for CBLOF, $K$-means, PCA, IF, and NED are (0.80, 0.84), (0.82, 0.85), (0.86, 0.89), (0.90, 0.93), and (0.95, 0.97) based on BTD and ETC datasets, respectively. While running the Block Hunter framework with each ML model, we obtain a global model whose parameters are frequently updated via the FedAvg approach [24].

Table IV presents the hunting of anomalies in global models using NED as the local model. This table shows the moment where the Block Hunter framework can hunt an anomaly while doing transactions. This consists of $K = 30, 40, 50$ clusters and 1 to 35 transactions per second for 100 s. Based on the cluster-based structure in the Block Hunter, it is almost certain that this system’s accuracy is acceptable during anomaly hunting, as
shown in Table IV. The Block Hunter framework also works perfectly as the number of transactions and clusters increases. We also evaluated the performance of the Block Hunter on several IIoT standard datasets as shown in Table V. The model performance was evaluated using different ML models namely K-means, PCA, CBLOF, IF, and NED on GP and SWaT datasets. NED has the highest accuracy as it preserves data encoding/decoding.

Blockchain-based IIoT networks are the underlying technology for the future smart factories, hence, an emerging attack target, which shows the significance of this work. To the best of our knowledge, the Block Hunter is the first federated threat hunting model in IIoT networks that identifies anomalous behavior while preserving privacy. We used FL to build a threat hunting framework that utilizes a cluster-based architecture to formulate an anomaly detection combined with several ML models. Our results indicate the superior performance of our model in automatically hunting for anomalies while preserving data privacy.

VI. Conclusion

In this article, we developed the Block Hunter framework to hunt anomalies in blockchain-based IIoT smart factories using an FL approach. The Block Hunter used a cluster-based architecture to reduce resources and improve the throughput of blockchain-based IIoT networks hunting. The Block Hunter framework was evaluated using a variety of ML algorithms (NED, IF, CBLOF, K-means, and PCA) to detect anomalies. We also examined the impacts of block generation interval, block size, and different miners on the performance of the Block Hunter. Using generative adversarial networks to design and implement a block hunter-like framework would be an interesting future research work. Furthermore, designing and applying IIoT-related blockchain networks with different consensus algorithms would also be worth investigating in the future.

References

[1] J. Wan, J. Li, M. Imran, D. Li, and F. e Amin, "A blockchain-based solution for enhancing security and privacy in smart factory," IEEE Trans. Ind. Informat., vol. 15, no. 6, pp. 3652–3660, Jun. 2019.

[2] F. Scicchitano, A. Liguori, M. Guarascio, E. Ritacco, and G. Manco, "Blockchain attack discovery via anomaly detection," Consiglio Nazionale delle Ricerche, Istituto di Calcolo e Reti ad Alte Prestazioni, 2019.

[3] Q. Xu, Z. He, Z. Li, M. Xiao, R. S. M. Goh, and Y. Li, “An effective blockchain-based, decentralized application for smart building system management,” in Real-Time Data Analytics for Large Scale Sensor Data. Amsterdam, The Netherlands: Elsevier, 2020, pp. 157–181.

[4] B. Podgorelec, M. Turkanović, and S. Karakati, “A machine learning-based method for automated blockchain transaction signing including personalized anomaly detection,” Sensors, vol. 20, no. 1, 2020, Art. no. 147.

[5] A. Quintal, “VeriBlock foundation discloses mess vulnerability in ethereum classic blockchain,” VeriBlock Foundation. Accessed: Jul. 08, 2021. [Online]. Available: https://www.pnewire.com/news-releases/veriblock-foundation-discloses-mess-vulnerability-in-ethereum-classic-blockchain-301327998.html

[6] M. Saad et al., “Exploring the attack surface of blockchain: A comprehensive survey,” IEEE Commun. Surveys Tuts., vol. 22, no. 3, pp. 1977–2008, Jul.—Sep. 2020.

[7] R. A. Sater and A. B. Hamza, “A federated learning approach to anomaly detection in smart buildings,” ACM Trans. Internet Things, vol. 2, no. 4, Aug. 2021, doi: 10.1145/3467981.

[8] O. Shafiq, “Anomaly detection in blockchain,” M.S. thesis, Tampere Univ., Tampere, Finland, 2019.

[9] A. Yazdinejada, R. M. Parizi, A. Dehghantanha, and H. Karimipour, “Federated learning for drone authentication,” Ad Hoc Netw., vol. 120, 2021, Art. no. 102574.

[10] D. Droseva, V. Rimmer, I. Tsigenopoulos, J. Sporen, W. Joosen, and E. Ilie-Zudor, “Chained anomaly detection models for federated learning: An intrusion detection case study,” Appl. Sci., vol. 8, no. 12, 2018, Art. no. 2663.

[11] L. Tan, H. Xiao, K. Yu, M. Aloqaily, and Y. Jararweh, “A blockchain-empowered crowdsourcing system for 5G-enabled smart cities,” Comput. Standards Interfaces, vol. 76, 2021, Art. no. 103517.

[12] L. Tseng, X. Yao, S. Otoum, M. Aloqaily, and Y. Jararweh, “Blockchain-based database in an IoT environment: Challenges, opportunities, and analysis,” Cluster Comput., vol. 23, no. 3, pp. 2151–2165, 2020.

[13] M. Signorini, M. Pontecorvi, W. Kanoun, and R. Di Pietro, “BAD: A blockchain anomaly detection solution,” IEEE Access, vol. 8, pp. 173481–173490, 2020.

[14] S. Iyer, S. Thakur, M. Dixit, R. Katkam, A. Agrawal, and F. Kazi, “Blockchain and anomaly detection based monitoring system for enforcing wastewater reuse,” in Proc. 10th Int. Conf. Comput., Commun. Netw. Technol., 2019, pp. 1–7.

[15] S. Sayadi, S. B. Rejeb, and Z. Choukair, “Anomaly detection model over blockchain electronic transactions,” in Proc. 15th Int. Wireless Commun. Mobile Comput. Conf., 2019, pp. 895–900.

[16] Z. Il-Agure, B. Attallah, and Y.-K. Chang, “The semantics of anomalies in IoT integrated blockchain network,” in Proc. 6th HICT Inf. Technol. Trends, 2019, pp. 144–146.

[17] F. Scicchitano, A. Liguori, M. Guarascio, E. Ritacco, and G. Manco, “A deep learning approach for detecting security attacks on blockchain,” in Proc. Int. Conf. Cybersecur., 2020, pp. 212–222.

[18] T. R. Gadekallu et al., “Blockchain for edge of things: Applications, opportunities, and challenges,” IEEE Internet Things J., vol. 9, no. 2, pp. 964–988, Jan. 2022.

[19] T. D. Nguyen, S. Marchal, M. Miettinen, H. Fereidooni, N. Asokan, and A. R. Sadeghi, “DIO: A federated self-learning anomaly detection system for IoT,” in Proc. IEEE 39th Int. Conf. Distrib. Comput. Syst., 2019, pp. 756–767.

[20] S. Li, Y. Cheng, Y. Liu, W. Wang, and T. Chen, “Abnormal client behavior detection in federated learning,” 2019, arXiv:1910.09933.

[21] R. Kumar et al., “Blockchain-federated-learning and deep learning models for COVID-19 detection using CT imaging,” IEEE Sens. J., vol. 21, no. 14, pp. 16301–16314, Jul. 2021, doi: 10.1109/JSEN.2021.3076676.

[22] H. Chai, S. Leng, Y. Chen, and K. Zhang, “A hierarchical blockchain-enabled federated learning algorithm for knowledge sharing in internet of vehicles,” IEEE Trans. Intell. Transp. Syst., vol. 22, no. 7, pp. 3975–3986, Jul. 2021.

[23] M. Alalhail, S. P. RM, P. M., P. K. R. Madakkittu, T. R. Gadekallu, and Q.-V. Pham, “Federated learning for cybersecurity: Concepts, challenges, and future directions,” IEEE Trans. Ind. Informat., vol. 18, no. 5, pp. 3501–3509, May 2022.

[24] H. B. McMahan, E. Moore, D. Ramage, S. Hampson, and B. Agüera y Arcas, “Communication-efficient learning of deep networks from decentralized data,” in Proc. 20th Int. Conf. Artif. Intell. Statist., ser. Proc. Mach. Learn. Res., A. Singh and J. Zhu, Eds., 2017, pp. 1273–1282. [Online]. Available: https://proceedings.mlr.press/v54/mcmahan17a.html

[25] J. Konečný, H. B. McMahan, F. X. Yu, P. Richtárik, A. T. Suresh, and D. Bacon, “Federated learning: Strategies for improving communication efficiency,” 2016, arXiv:1610.05492.
[26] N. Moussa and A. E. B. El Alaoui, “An energy-efficient cluster-based routing protocol using unequal clustering and improved ACO techniques for WSNs,” Peer-to-Peer Netw. Appl., vol. 14, pp. 1334–1347, 2021.

[27] A. Yazdinejad, R. M. Parizi, G. Srivastava, A. Dehghantanha, and K.-K. R. Choo, “Energy efficient decentralized authentication and verification in internet of underwater things using blockchain,” in Proc. IEEE Globecom Workshops, 2019, pp. 1–6.

[28] V. Le, T. P. Quinn, T. Tran, and S. Venkatesh, “Deep in the bowel: Highly interpretable neural encoder-decoder networks predict gut metabolites from gut microbiome,” BMC Genomics., vol. 21, no. 4, pp. 1–15, 2020.

[29] S. Golovkine, N. Klutchnikoff, and V. Patleia, “Clustering multi-variate functional data using unsupervised binary trees,” Comput. Statist. Data Anal., vol. 168, pp. 107376, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0167947321002103

[30] H. Abdi and L. J. Williams, “Principal component analysis,” Wiley Interdiscip. Rev., Comput. Statist., vol. 2, no. 4, pp. 435–459, 2010.

[31] K. P. Sinaga and M.-S. Yang, “Unsupervised k-means clustering algorithm,” IEEE Access, vol. 8, pp. 80716–80727, 2020.

[32] I. P. Turnipseed, “A new SCADA dataset for intrusion detection research,” Master thesis, Mississippi State Univ., Mississippi State, MS, USA, 2015.

[33] R. Taormina et al., “Battle of the attack detection algorithms: Disclosing cyber attacks on water distribution networks,” J. Water Resour. Plan. Manage., vol. 144, no. 8, 2018, Art. no. 04018048.

Abbas Yazdinejad received the B.Sc. degree in computer engineering from the Shahid Bahonar University of Kerman, Kerman, Iran, in 2014, and the M.Sc. degree in computer engineering from the University of Isfahan, Isfahan, Iran, in 2016. He is currently working toward the Ph.D. degree with Smart Cyber-Physical Lab, University of Calgary, Calgary, AB, Canada.

He is currently associated with the Cyber Science Lab, School of Computer Science, University of Guelph, Guelph, ON, Canada and Decentralized Science Lab (DSL), Kennesaw State University, Kennesaw, GA, USA. His research interests include cybersecurity, blockchain, software-defined networking, Internet of Things, and field-programmable gate array design.

Ali Dehghantanha (Senior Member, IEEE) received the B.Sc. degree in software engineering from the Azad University of Mashhad, Mashhad, Iran, in 2005, the M.Sc. and Ph.D. degrees in security in computing from the University Putra, Kembangan, Selangor, Malaysia, in 2008 and 2011, respectively.

He is a Cyber-Entrepreneur in Cybersecurity, a Canada Research Chair in Cybersecurity and Threat Intelligence, and an Associate Professor in Cybersecurity with the University of Guelph, Guelph, ON, Canada. He is the Director with Cyber Science Lab, a research lab dedicated to advance research and training in cybersecurity, and the Director and Founder of the Master of Cybersecurity and Threat Intelligence program, University of Guelph.

Reza M. Parizi (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees in computer science and the Ph.D. degree in software engineering from the Universiti Putra, Kembangan, Selangor, Malaysia, in 2005, 2008, and 2012, respectively.

He is the Director with the Decentralized Science Lab, Kennesaw State University (KSU), Kennesaw, GA, USA. He is a consummate technologist and cybersecurity researcher with an entrepreneurial spirit. Prior to joining KSU, he was with the New York Institute of Technology. His research interests include R&D in decentralized artificial intelligence, federated learning, blockchain systems, smart contracts, and emerging issues in the practice of secure software-run world applications.

Dr. Parizi is a Senior Member of the IEEE Blockchain Community and ACM.

Mohammad Hammoudeh (Senior Member, IEEE) received the B.Sc. degree in computer communications from Arts Sciences Technology University, Beirut, Lebanon, in 2004, the M.Sc. degree in advanced distributed systems from the University of Leicester, Leicester, U.K., in 2006, the Postgraduate Certificate in academic practice from Manchester Metropolitan University, Manchester, U.K., in 2011, and the Ph.D. degree in computer science from the University of Wolverhampton, Wolverhampton, U.K., in 2008.

He is the Saudi Aramco Chair Professor of cyber security with the Information Computer Science Department, King Fahd University of Petroleum Minerals, Dhahran, Saudi Arabia. His research interests include centered around the applications of zero trust security to Internet-connected critical national infrastructures, blockchains, the Internet of Things/cyber physical systems and other complex highly decentralized systems.

Dr. Hammoudeh is the founder and Co-Editor-in-Chief of ACM’s journal Distributed Ledger Technology: Research Practice.

Hadis Karimipour (Senior Member) received the Ph.D. degree in electrical engineering from the University of Alberta, Edmonton, AB, Canada, in June 2016.

She is the Director with the Smart Cyber-Physical (SCPS) Lab, an Associate Professor and Chair in secure and reliable networked engineering systems with the Department of Electrical and Software Engineering, University of Calgary, Calgary, AB. Before joining the University of Calgary in July 2021, she was an Assistant Professor with the School of Engineering, University of Guelph, in 2017–2021, and a Postdoctoral Fellow with the University of Calgary in 2016–2017. She has authored and co-authored 2 books, 30 journal articles, 24 book chapters, and 30 conference articles in top IEEE journals and conferences.

Dr. Karimipour was the recipient of the prestigious Queen Elizabeth II Scholarship (2014 and 2015) in support of her Ph.D. research. She is among the pioneers of using artificial intelligence and machine/deep learning for security analysis of critical infrastructure.

Gautam Srivastava (Senior Member, IEEE) received the B.Sc. degree in math and computer science from Briar Cliff University, Sioux City, IA, USA, in 2004, and the M.Sc. and Ph.D. degrees in computer science from the University of Victoria in Victoria, BC, Canada, in 2006 and 2012, respectively.

He is currently an Associate Professor with Brandon University, Brandon, MB, Canada, where he is currently involved in various professional and scholarly activities. He is popularly known for his research in the field of cryptography, data mining, security and privacy, and blockchain Technology. In his five years of research academic, he has authored and co-authored a total of 180 papers in high-impact conferences in many countries and in high status journals (SCI, SCIE).

Dr. Srivastava has delivered invited guest lectures on Big Data, Cloud Computing, Internet of Things, and Cryptography at many universities worldwide. He is an Editor of several SCI/SCIE journals. He is an Associate editor for many IEEE journals.