Blockchain-Enabled Federated Learning on Kubernetes for Air Quality Prediction Applications

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Abstract

The biggest realization of the Machine Learning (ML) in societal applications, including air quality prediction, has been the inclusion of novel learning techniques with the focus on solving privacy and scalability issues which capture the inventiveness of tens of thousands of data scientists. Transferring learning models across multi-regions or locations has been a considerable challenge as sufficient technologies were not adopted in the recent past. This paper proposes a Blockchain- enabled Federated Learning Air Quality Prediction (BFL-AQP) framework on Kubernetes cluster which transfers the learning model parameters of ML algorithms across distributed cluster nodes and predicts the air quality parameters of different locations. Experiments were carried out to explore the frame- work and transfer learning models of air quality prediction parameters. Besides, the performance aspects of increasing the Kubernetes cluster nodes of blockchains in the federated learning environment were studied; the time taken to establish seven blockchain organizations on top of the Kubernetes cluster while investigating into the federated learning algorithms namely Federated Random Forests (FRF) and Federated Linear Regression (FLR) for air quality predictions, were revealed in the paper.

Keywords: Air Quality; Blockchain; Federated Learning; Kubernetes; Smart cities;

1. INTRODUCTION

In the wake of the air pollution causing damages to the smart city dwellers in the past, an agglomeration of IoT-enabled solutions has evolved in the recent past – smart air quality monitoring, smart air quality-aware room reservations, smart air-quality aware tourism planning, and so forth. Many smart cities have adopted indoor and outdoor policies to restraint from evolving health hazards such as asthma, chronic pulmonary disorders, and so forth, due to the emissions of air toxic, including SO_2 or CO_2 from various sources such as industries and road traffics [1-3].

Air quality monitoring using IoT-enabled sensors, in general, could not be established in widespread geo-spatial monitoring points due to the involving sensing costs and communication issues. Smart cities, which aims for establishing a sustainable environment, attempts to deliver a real-time data acquisition mechanism either through frequent monitoring or prediction approaches – i.e., obviously, prediction-aware solutions with minimal sensor data are required in smart cities [4, 5].

In the past, centralized training models and prediction solutions had earned the minds of data scientists [6, 7], including air quality prediction researchers [8]. However, the emergence of a few notable challenges in recent years has demanded the need for decentralized training approaches. For instances, the challenges such as:

1) evidence noticed in latency while transferring a large volume of data to the centralized training locations;

2) hurdle levied in transferring privacy data to the centralized cloud instances;

3) increase in the energy consumption of air quality monitoring application; and so fort

Federated learning, in recent years, has enabled a decentralized learning platform signalling a path to resolve the previously mentioned challenges that are possible through the traditional centralized training models – i.e., consequently, the utilization of the federated learning approach has motivated several data scientists to decentralize the learning processes.

This paper proposes a federated learning-based decentralized learning mechanism for predicting the air quality parameters of different locations. It proposes a blockchain-enabled federated learning framework named BFL-AQP framework in which the learning parameters of the algorithm are quickly transferred to the prediction environments through blockchains. The framework applies permissioned blockchain using hyperledger fabric on Kubernetes cluster to establish scalable networking among blockchains.

The experiments were carried out at the IoT cloud research laboratory such that multiple peer organizations of blockchains were established on Kubernetes cluster to transfer the modeling parameters through blockchain ledgers. The article pinpointed the performance bottlenecks of utilizing more number of organizations, which represent various smart cities, and the involvement of peer nodes to record the modeling parameters on the immutable database of the blockchain network.

The rest of the paper is described as follows: Section 2 provides a state-of-the-art research in the federated learning domain for IoT-enabled societal applications; Section 3 highlights the proposed Blockchain-enabled Federated Learning environment for monitoring air quality in smart cities; Section 4 describes the blockchain utility for higher availability of modeling parameters among smart cities; Section 5 illustrates the experimental setup and the evaluation results; and, finally Section 6 provides a few conclusions and the outlooks.

2. RELATED WORKS

Machine Learning algorithms have influenced a large volume of working domains in recent years. The major concerns of traditional machine learning approaches such as poor scalability, privacy issues, latency issues, energy consumption issues, and so forth, have been revisited with innovative perspectives
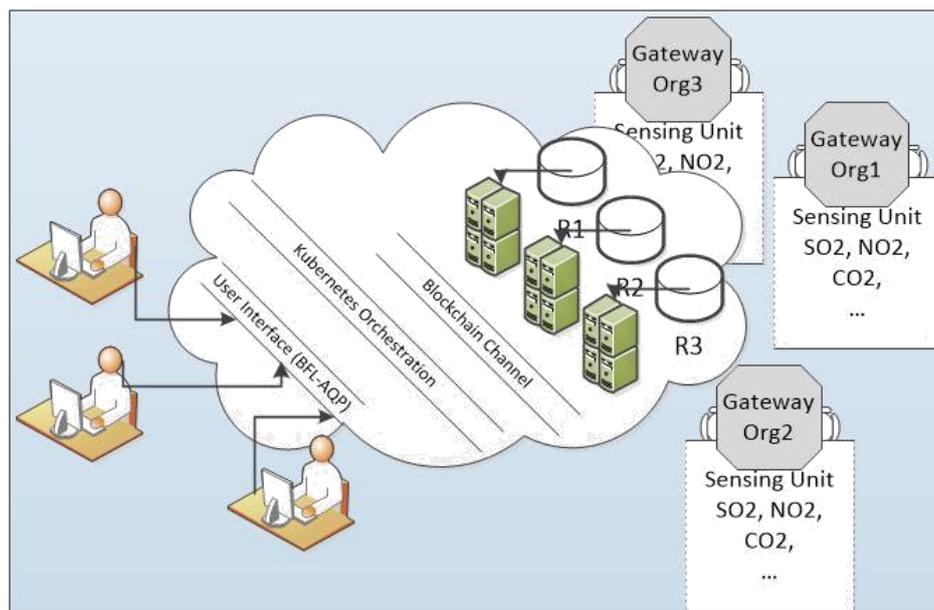
Figure. 1.   BFL-AQP Framework

Besides, it has been reported recently that the data processing and analytics approaches have to deal with evolving zettabytes of data [9]. Understanding the utility benefits of Federated Learning, researchers have applied the decentralized learning approach in various domains. For instance, Sumudhu et al. [10] have applied the federated learning approach in the vehicular communication domain to target the latency issues; Linghe et al. [11] have applied federated learning to analyze the assembly line features in a collaborative manner in an automobile industry; Yang et al [12] have attempted to analyze objects in a distributed manner; Youris et al. [13] have utilized federated learning approach for predicting the energy demand for electric vehicles, and so forth.

In addition, FL application could also be rewarded for elegantly utilizing the energy constraint resources such as edge nodes or computing nodes for completing the learning processes. For instance, Latif et al. [14] have highlighted the application of an incentive mechanism in FL.

 A few researchers have endeavoured to study the performance improvements of federated learning and associated algorithms. For instance, Nicolas et al [15] have studied the impact of communication cost on distributed machines. A few works have been carried out to offload appropriate workloads to apt computing machines. Typically, authors of [16] studied the

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impact of offloading appropriate tasks to computing nodes considering various aspects, including the completion time.

Also, a few authors have further dived into the methods to reduce the energy consumption of applications [17]. Fu et al [18] and Ishtiaque et al [19] proposed caching mechanism to improve the energy efficiency of IIoT applications. Recently, Shajulin et al. has expressed the energy efficiency aspects of federated learning algorithms [20].

As observed, the application of federated learning in various domains such as IoT, IIoT, deep learning, and so forth, with several standalone approaches for improving the performance, including the energy consumption issues, have been discussed in the recent past. However, the utilization of blockchains to quickly transfer the modeling parameters was not widely studied. Recently, Gaofeng et al [21] have revealed the utilization of blockchains for transferring the learning inferences in a decentralized fashion without a centralized trusted server; in [22], authors have utilized blockchain in IIoT as a secure data sharing mechanism for providing federated learning aspects. Very recently, authors of [23] have attempted to transfer the learning models using Kubernetes cluster for improving the scalability aspect of learning algorithms.

In fact, the application of blockchains on Kubernetes cluster could improve the easiness of hosting scalable containers and providing secure policies/transactions. Jungsu et al [24] have studied the impact of placing microservices on distributed kubernetes clusters in the recent past. A very few researchers have delved into the importance of including kubernetes cluster for hosting blockchain services.

This article attempted to utilize blockchains for transferring the modeling parameters rather than transferring the data across a centralized server. The approach was focused on air quality prediction of smart cities in a decentralized manner so that the latency issues and privacy issues could be avoided in the learning processes.

3. BFL-AQP FRAMEWORK

This section highlights the proposed BFP-AQP framework that enables blockchain-supported transfer of modeling parameters across blockchain network hosted on Kubernetes clusters for

the decentralized learning processes. The primordial objectives of the proposed framework are listed as follows:

- to transfer the learning models or parameters across distributed nodes so that the sensor data are localized within regions, and

- to transfer the knowledge of air quality prediction information using the secure transactions of blockchains in a performance-efficient manner.

The major components involved in the BFL-AQP frame-work and their functionalities are given below:

1) *Sensing Unit:* The sensor unit consists of sensors to monitor air quality values such as NO2, SO2, Particulate Matters (PM2.5) and so forth. The sensor data are transferred through gateways to edge or cloud services. However, it is to be observed that not all locations in the smart cities have to be equipped with sensors owing to cost efficiency and site references.

2) *Cluster Unit:* The decentralized learning of air quality sensor data for different locations is enabled by connecting multiple compute nodes, either raspberry pi or powerful compute machines, to frame a cluster of de-vices. The cluster unit is established using kubernetes or similar cluster orchestration tools.

3) *Blockchain Unit:* A permissioned blockchain is powered on the Cluster Unit comprising of docker ma-chines, VMs, or server instances. The Blockchain Unit encompasses chaincodes, i.e., business logics, to invite transactions in the form of learning modeling parameters for registering them into the blockchain ledgers so that the information could be made available to the other regions.

4) *Networking Channels*: The compute nodes, either docker machines, VMs, or servers, are interconnected to frame a newer overlayed network on P2P connectivity setup. These networking channels offer specific isolated connection of nodes for transferring the blockchain ledger information within the connected blockchain networked nodes.

5) *User-Interface:* The user-interface assists the user of BFL-AQP framework to register into the decentralized learning platform. The users could view the status of the learning parameters adopted on different locations and the corresponding accuracy information due to the localized sensor data of various regions.

The components of BFL-AQP framework are responsible to transfer the modeling parameters of federated learning algorithms such as Federated Random Forests (FRF) and Federated Linear Regression (FLR) to different regions R_n through blockchain ledger *L*. Figure 1 provides a pictorial representation of the proposed BFL-AQP framework and its components.

4. LEARNING MODEL TRANSFER -- Decentralized Approach

This section explains the procedure to setup a decentralized learning platform using kubernetes clusters; the federated learning algorithms involved in the framework; the establishment of hyperledger fabric-based permissioned blockchain on the Kubernetes cluster; and, the processes involved in transferring modeling parameters across different regions to adopt decentralized learning using blockchains on Kubernetes clusters.

4.1. KUBERNETES CLUSTER

The hyperledger fabric-based permissioned blockchain needs to be spread across a distributed network so that modeling parameters could be transferred across regions of different locations such as smart cities. In fact, the hyperledger fabric establishes the blockchain network using containers that represent organizations. The service discovery of containers, hosting containers on multi-party domains, configuration of containers using YAML files, and so forth are arduous tasks when multi-organizational deployment of blockchains were considered.

Kubernetes, in general, has the benefits of orchestrating containers housed on multiple nodes within a short span of time [25]; it has capabilities of scaling depending on the requirement of nodes for the applications. In modern cloud environments, the application of Kubernetes cluster has manifested several researchers and developers [26].

The configuration settings of the Kubernetes cluster are represented in YAML files such that the required port settings and replica information of nodes, including master node, could be

initiated using *kubeadm* tool. Initially, the master node of the Kubernetes cluster needs to be instantiated before the worker nodes join the master node for enabling the cluster.

4.2. FEDERATED LEARNING ALGORITHMS

Traditionally, learning algorithms such as Random Forests (RF) and Linear Regression (LR) are executed on centralized nodes. However, in federated learning, decentralized learning has to be supported – i.e., the modeling parameters are transferred to decentralized compute nodes so that the data are not transferred to the centralized nodes for learning data.

In this work, Federated Random Forest (FRF) and Federated Linear Regression (FLR) are implemented with the support of blockchains. The federated algorithms FRF and FLR utilizes random forests and linear equations between the dependent and independent variables of datasets as similar to the RF and LR approaches. In addition to the synopsis of the traditional learning approaches, the federation component of the algorithms is included in the framework – i.e., the federation component of algorithms promotes the sharing of modeling parameters and obtaining a global learning at the end of the decentralized learning processes.

The functional details of FRF and FLR are described as below:

1) *FRF – Federated Random Forests:* The FRF algorithm attempts to learn air quality sensor values from the regional locations based on the modeling parameters such as NO2, SO2, and so forth, using the bagging approach. The modeling parameters are localized for regions such that the findings are shared to the global inference engine to prepare the final learning about the air quality information.

2) *FLR – Federated Linear Regression:* As similar to FRF algorithm, FLR endeavors to learn based on linear functions in a distributed manner using Kubernetes clusters. The training processes of FLR are bound to the data available from the localized region.

4.3. BLOCKCHAIN-ENABLED MODEL TRANSFER

The findings of the learning models and the prediction accuracy information of learning models need to be shared across geographically spread multi-organizational institutions. Similarly, there could be different policies set up by the local smart cities to infer the air quality sensor data which need to be evaluated based on the prediction findings. For instance, the air quality value measured by sensors nearer to a factory unit might have a different acceptance threshold value among the smart city citizens.

In order to cope with the different possible local policies across regions and to protect the data within the regions, per-missioned blockchains are established in BFL-AQP frame-work.

4.4. NECESSITY OF KUBERNETES

In this work, blockchains are hosted on Kubernetes clusters while sharing the federated learning models across regions. The major advantages of including Kubernetes in the framework are multi-fold:

1) Blockchain processes and policies are containerized and ported across the Kubernetes cluster at ease;

2) Multiple replicas of containers are easily distributed or scheduled across regions, especially in smart city environments using Kubernetes cluster environments; and,

3) Blockchain ledgers could be easily transported across multi-organizations without security issues under the purview of the established Kubernetes clusters.
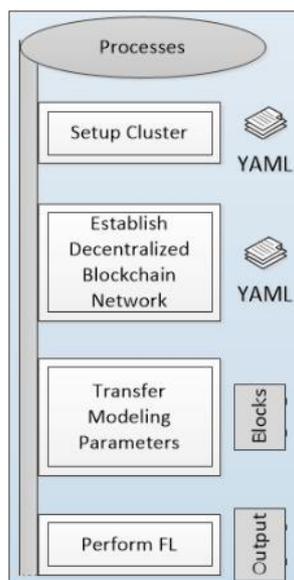
4.5 PROCESSES INVOLVED

Figure. 2. Decentralized Federated Learning Processes using Blockchain on Kubernetes for BFL-AQP

The entire processes involved in the framework to promote decentralized learning of air quality parameters in distributed regions such as smart cities are listed below:

1) At first, the Kubernetes cluster need to be enabled for multi-organizational domains or locations;

2) Next, the permissioned blockchain docker containers along with the policies/chain codes has to be established on the Kubernetes overlay networks;

3) In the meantime, air quality is monitored from different regions/locations and the air quality monitoring results are stored for future predictions;

4) Next, the learning inferences, the independent variables utilized for predictions, and the policies are initiated as transactions to blockchains which need to be approved by multi-participants of blockchains;

5) Next, the federated learning model parameters of FLR or FRF are stored into the blockchain ledger depending on the approval from various approving authorities of the blockchain;

6) Finally, depending on the approved learning model parameters, the air quality values are predicted for certain locations where monitoring sites are not available. Figure 2 details on the processes involved in the proposed framework in a pictorial form.

5. EXPERIMENTAL RESULTS

This section reveals the importance of the proposed BFL-AQP framework in two dimensions: i) the findings of prediction algorithms and ii) the performance aspects of increasing peers and policies in blockchains.

5.1. PREDICTION FINDINGS – FEDERATED ALGORITHMS

Datasets from three different locations, namely, Tamilnadu, Kerala, and Odisha, were considered from data.gov.in [27]. For the datasets of size varying from 8000 to 25000, the SO2 and NO2 values were predicted with different training parameters.

For instance, the Tamilnadu region utilized NO2, Location, monitoring station code, and RSPM while predicting SO2 air quality value; the Kerala region utilized NO2, Date of Monitoring, monitoring station code, and RSPM while predicting SO2. It could be observed that the modeling parameters utilized for training the datasets varied in the Federated algorithmic implementations.

The accuracy values obtained by the FRF and FLR algorithms are shown in the Table I.

Table 1 R^2 Values Obtained For Federated Learning Algorithms –FRF And FLR

ODISHA		
FRF	99.3	97.5
FLR	79.4	77.3
KERALA		
FRF	96.5	94.4
FLR	80.2	79.4
TAMILNADU		
FRF	98.5	97.3
FLR	82.8	79.5

It is to be noticed that the accuracy values of prediction algorithms varied while modifying the modeling parameters for different smart cities. However, choosing the apt modeling parameters was determined by the blockchain policies governed by multiple actors of the smart cities.

5.2. PERFORMANCE IMPACTS – BLOCKCHAIN

It was interesting to understand the necessity of utilizing blockchain for transferring the modeling parameters in the federated learning ecosystem. Hence, performance studies were carried out while transferring the independent and dependent values of learning algorithms as transactions. The transactions were recorded in the immutable blockchain database.

Towards this end, experiments were held by establishing a Kubernetes cluster consisting of seven blockchain organizations (also, named as worker nodes) and a master node. Each organization was deployed with three peer nodes represented as P0, P1, and P2. The peer nodes contained docker machines on the worker nodes of the Kubernetes cluster. The worker nodes were physical machines with i7 processors clustered at the IoT cloud research laboratory.

1) *Kubernetes Cluster Formation:* As mentioned earlier, the organizations hold chaincodes, the smart contract policies, for determining the necessity of registering the transactions into the blockchain database.

    The entire organizations and docker machines were tied to a single channel so that the ledger was visible to all participating blockchain members – i.e., the transactions mentioning the modeling parameters of different regions were visible to all regions involved in the federated learning processes.

    From Figure 3, it could be observed that the creation of the master node was 131.01 seconds; the worker nodes joining the Kubernetes master node took 41.86 seconds on average. In the experiments, seven worker nodes were utilized from various networks of the laboratory to mimic the different air quality monitoring stations.
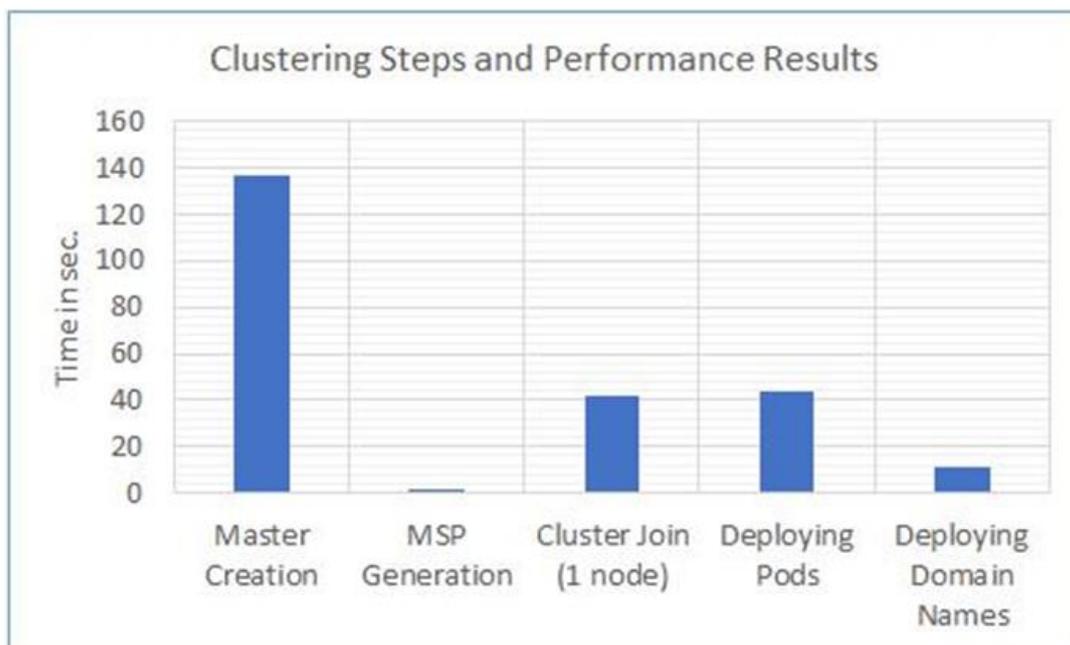
Figure. 3.   Performance Study on the Clustering Steps of Blockchain on Kubernetes

2) *Channel Formation:* Among all available peer nodes in the blockchain network, one peer was responsible to establish the channel and the other peer nodes joined the channel for sharing the blockchain ledger. The peer node that established the channel took 10.63 seconds and the other nodes had 2.52 seconds on average to join the established channel.

Figure 4 revealed the time required for establishing and joining the channel of the blockchain network.
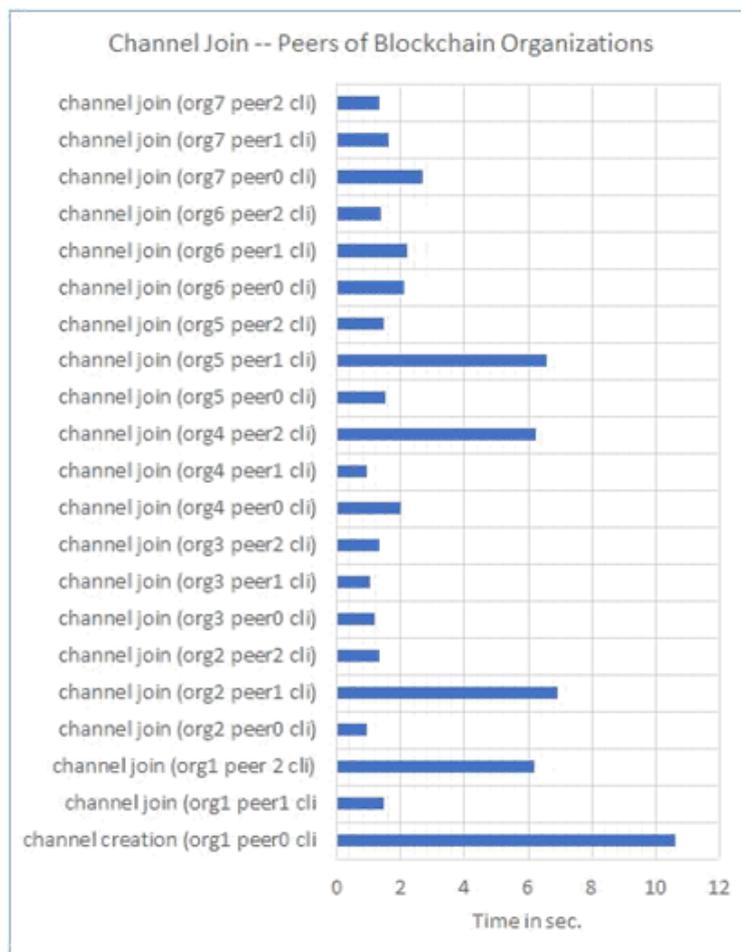
Figure. 4.   Channel Creation and Joining

3) *Chaincode Instantiation and Invocation:* The chain-code policies need to be installed on all available peer nodes of the blockchain network. Figure 5 revealed the time required for installing the chaincode policies in peer nodes.

The modeling parameters of the federated learning algorithms represented in the form of blockchain transactions need to be invoked before performing distributed learning on respective decentralized regions. The invoke times for 100 to 1000 continuous transactions are represented in Table II. It could be observed that the increase in the number of transactions could increase the time for executions. For instance, invoking 1000 transactions from the blockchain database by the client of Org6 P0 was 209.42 seconds.
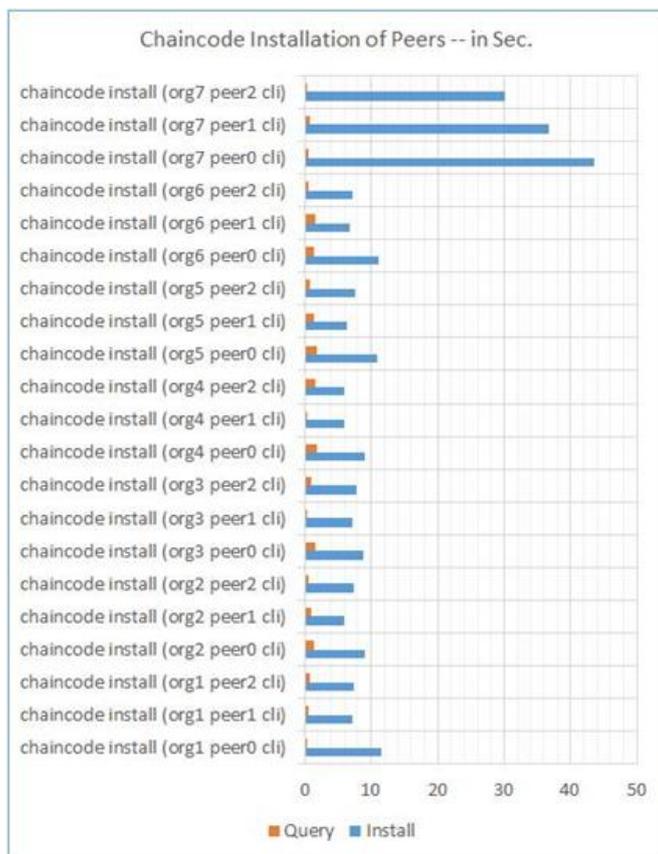
Figure. 5.   Chaincode Installation on Peer Nodes

4) *Blockchain Permissions*: Organizations representing different smart cities might have different opinions on accepting the air quality values. For instance, the acceptance of an SO2 value in a vicinity could be comparatively larger than the other locations. This is due to the fact that the regional celebrations in certain localized regions might be permitted/acceptable by smart city officials. Similarly, the modeling parameters utilized in the learning processes could vary across regions because of the availability of the localized sensor data.

Accordingly, the approval processes for registering a transaction into the immutable database of the blockchain network were accomplished. In each organization, at least one peer node has to serve as an approver. In the experiments, peer 0 of every smart city organizations was recognized to serve as the approvers.

Table 2 Invoke Time Of Organizations For No.Of Transactions In Sec.

	100	200	300	400	500	600	700	800	900	1000
(org1 peer0 cli)	15.468	29.151	46.127	58.222	74.269	88.684	104.332	123.409	147.115	160.991
(org1 peer1 cli)	14.685	29.491	43.978	58.235	73.495	87.287	102.49	118.554	149.118	164.278
(org1 peer2 cli)	15.641	28.658	42.541	60.201	74.109	89.145	100.898	116.674	152.534	177.474
(org2 peer0 cli)	14.062	28.841	41.419	56.881	69.498	88.831	98.248	111.866	138.332	152.855
(org2 peer1 cli)	14.107	29.054	41.502	57.745	67.973	86.279	94.818	111.815	133.368	150.14
(org2 peer2 cli)	13.929	28.576	41.458	56.127	70.116	83.787	98.978	110.134	134.987	148.934
(org3 peer0 cli)	15.556	29.449	43.785	60.262	73.213	88.684	96.983	122.853	144.079	159.473
(org3 peer1 cli)	16.927	33.252	44.347	59.495	73.779	86.777	104.336	118.965	144.134	161.32
(org3 peer2 cli)	14.878	30.031	44.351	59.274	75.647	90.572	103.115	117.559	147.657	162.504
(org4 peer0 cli)	14.753	30.267	43.719	60.416	73.537	86.342	100.791	117.75	145.943	178.113
(org4 peer1 cli)	14.476	31.634	44.557	58.294	73.365	89.288	99.473	115.682	150.189	176.802
(org4 peer2 cli)	14.472	31.057	44.416	59.778	73.628	93.94	101.011	122.933	148.173	180.031
(org5 peer0 cli)	17.072	31.196	44.611	66.172	80.248	93.569	110.187	128.241	142.45	167.917
(org5 peer1 cli)	15.845	33.945	48.301	65.305	79.893	96.04	111.697	131.145	142.881	162.42
(org5 peer2 cli)	15.539	34.557	50.641	66.406	78.032	92.119	110.035	127.774	137.098	159.437
(org6 peer0 cli)	15.355	36.861	45.711	61.768	78.394	94.746	101.905	130.387	184.183	209.424
(org6 peer1 cli)	14.917	31.131	45.014	59.938	78.591	95.112	105.303	129.569	182.811	204.939
(org6 peer2 cli)	15.866	31.426	45.127	62.796	79.308	95.938	104.979	127.295	188.132	213.581
(org7 peer0 cli)	15.803	32.364	47.243	62.934	79.938	94.681	113.272	126.624	143.378	166.286
(org7 peer1 cli)	16.097	31.334	45.927	62.326	76.996	93.985	108.582	124.588	140.284	158.202
(org7 peer2 cli)	16.179	30.595	48.879	60.613	76.03	94.985	109.904	126.471	138	158.697

The time taken by the approvers to approve the transactions – i.e., the decentralized learning model parameters – and, to commit the transaction into the blockchain database is shown in
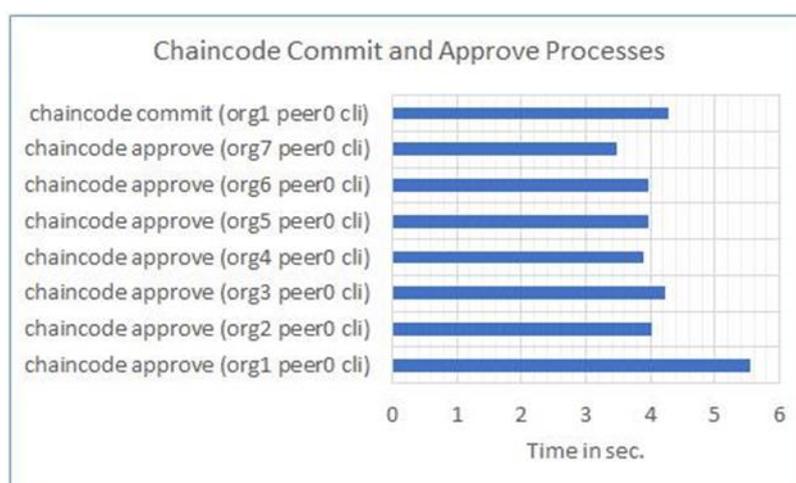

Fig. 6. Chaincode Commit and Approve Processes

Figure 6. It could be observed that the time taken to approve chaincodes differed among organizations – i.e., the time taken by the peer 0 of org 1 took over 5.5 seconds to approve the transaction when compared to the other peer nodes of the framework.

6. CONCLUSION AND OUTLOOKS

Society beneficial IoT applications, in general, require ro- bust learning mechanisms or software engineering practices. This paper proposed a BFL-AQP framework which applied permissioned blockchains on Kubernetes clusters to transfer air quality modeling parameters across multiple regions. The policies of blockchains were governed by distributed localized regions and the learning inferences were decentralized for improving security aspects. Experiments were carried out at IoT Cloud Research laboratory to manifest the importance of BFL-AQP framework. The performance aspects of transferring the learning models across regions using blockchains on the Kubernetes clusters were discussed. The experiments highlighted the involvement of the Kubernetes cluster and multi-organizational blockchain nodes on the cluster while predicting the air quality parameters in specific regions.

References

[1]   Mugunthan, S., and T. Vijayakumar. "Review on IoT based smart grid architecture implementations." Journal of Electrical Engineering and Automation 10, no. 1 (2019): 12-20.

[2]   Hengjinda, P., Dr Chen, and Joy Iong Zong. "An Intelligent Feedback Controller Design for Energy Efficient Air Conditioning System." Journal of Electronics and Informatics 2, no. 3 (2020): 168-174.

[3]   REDDY, M. RAMANA. "IoT BASED AIR AND SOUND POLLUTION MONITIORING SYSTEM USING MACHINE LEARNING ALGORITHMS." Journal of IoT in Social, Mobile, Analytics, and Cloud 2, no. 1 (2020): 13-25.

[4]   Hariharakrishnan, Jayaram, and N. Bhalaji. "Adaptability Analysis of 6LoWPAN and RPL for Healthcare applications of Internet-of-Things." Journal of ISMAC 3, no. 02 (2021): 69-81.

[5]   Lai, Kong-Long, and Joy Iong Zong Chen. "Development of Smart Cities with Fog Computing and Internet of Things." Journal of Ubiquitous Computing and Communication Technologies (UCCT) 3, no. 01 (2021): 52-60.

[6]   Revanth Rathan P., P. Krishna Reddy, Anirban Mondal: Discovering Diverse Popular Paths Using Transactional Modeling and Pattern Min- ing. 30th International Conference on Database and Expert Systems Applications, DEXA, pp. 327–337, 2019.

[7]   Jens P. Elsner, Christian Koerner, Friedrich K Jondral (2009) Centralized modeling of the communication space for spectral awareness in cog- nitive radio networks, in ACM SIGMOBILE Mobile Computing and Communications Review, Vol. 13(2), pp. 62–73,.

[8]   Shajulin Benedict, Serverless Blockchain Enabled Architecture for IoT Societal Applications, in IEEE Transactions on Computational Social Systems, Vol. 7, No. 5, pp. 1146–1158, doi:10.1109/TCSS.2020.3008995, 2020.

[9]   Tom Coughlin, Forbes Report on Data Explosion, in https://www.forbes.com/ sites/tomcoughlin/2018/11/27/175-zettabytes- by-2025/7fe3174d5459, Accessed in March 2020.

[10]   Sumudu Samarakoon, Mehdi Bennis, Walid Saad, mrouane Debbah, Distributed Federated Learning for Ultra-Reliable Low-Latency Vehic- ular Communications, IEEE Transactions on Communications, DOI: 10.1109/TCOMM.2019.2956472, 2019.

[11]   Linghe Kong, Xiao-Yang Liu, Hao Sheng, Peng Zeng, Guihai Chen (2020). Federated Tensor Mining for Secure Industrial Internet of Things, in IEEE Transactions on Industrial Informatics, Vol. 16,(3). pp. 2144 – 2153.

[12]   Yang Liu, Anbu Huang, Yun Luo, He Huang, Youzhi Liu, Yuanyuan Chen, Lican Feng, Tianjian Chen, Han Yu, Qiang Yang, FedVision: An Online Visual Object Detection Platform Powered by Federated Learning, in arXiv, https://arxiv.org/abs/2001.06202, March 2020.

[13]   Yuris Saputra, Hoang Dinh Thai, Diep Nguyen, Eryk Dutkiewicz, Markus Mueck, Srikathyayani Srikanteswara, Energy Demand Predic- tion with Federated Learning for Electric Vehicle Networks, in arXiv, https://arxiv.org/abs/1909.00907, accessed in March 2020.

[14]   Latif U. Khan, Shashi Pandey, Walid Saad, Zhu Han, Minh Nguyen, Choong Seon Hong, Nguyen Tran(2020). Federated Learning for Edge Net- works: Resource Optimization and Incentive Mechanism, in arXiv, https://arxiv.org/pdf/1911.05642.pdf

[15]   Nicolas Aussel, Sophie Chabridon, Yohan Petetin (2020). Combining Federated and Active Learning for Communication-efficient Dis- tributed Failure Prediction in Aeronautics, in arXiv preprint, https://arxiv.org/pdf/2001.07504.pdf.

[16]   Jianji Ren, HaichaoWang, TingTing Hou, Shuai Zheng, and Chaosheng Tang (2019). Federated Learning-Based Computation Offloading Optimization in Edge Computing-Supported Internet of Things, in IEEE Access, Vol. 7, pp. 69194 – 69201.

[17]   Minghua Wang, Lihua Zhu, Laurence T. Yang, Man Lin, Xianjun Deng, and Lingzhi Yi (2019). Offloading Assisted Energy-Balanced IoT Edge Node Relocation for Confident Information Coverage, in IEEE Internet of Things, Vol. 6(3), pp. 4482 – 4490.

[18]   Fu J., Liu Y., Chao HC, Bhargava B., and Zhag Z.,(2018) Secure data storage and searching for industrial IoT by integrating fog computing and cloud computing, in IEEE Trans. Ind. Informatics, Vol 14(10), pp. 4519– 4528, .

[19]   Ishtiaque A. Zahed M., Iftekhar Ahmad, Daryaoush Habibi, and Quoc Viet Phung (2019). Content caching in Industrial IoT: Security and Eneergy Considerations, IEEE Internet of Things Journal.

[20]   Shajulin Benedict, Energy Efficient Aspects of Federated Learning – Mechanisms and Opportunities, accepted in icSoftComp2020, Springer- CCIS series, 2020.

[21]   Gaofeng Hua, Zhu L., Wu J., Shen C., Zhou L. and Q. Lin,(2020) Blockchain- Based Federated Learning for Intelligent Control in Heavy Haul Railway, in IEEE Access, vol. 8, pp. 176830–176839.

[22]   Yunlong Lu, X. Huang, Y. Dai, S. Maharjan and Y. Zhang, Blockchain and Federated Learning for Privacy-Preserved Data Sharing in Industrial IoT, in IEEE Transactions on Industrial Informatics, vol. 16, no. 6, pp. 4177–4186, doi: 10.1109/TII.2019.2942190, 2020.

[23]   Pekka Pakkonen, Daniel Pakkala, Jussi Kiljander, and Roope Sarala (2021). Architecture for Enabling Edge Inference via Model Transfer from Cloud Domain in a Kubernetes Environment, in Future Internet, Vol   13(1), pp. 1–24.

[24]   Jungsu Han, Y. Hong and J. Kim (2020). Refining Microservices Placement Employing Workload Profiling Over Multiple Kubernetes Clusters, in IEEE Access, Vol. 8, pp. 192543–192556.

[25]   Kubernetes Documentation, in https://kubernetes.io/docs/concepts/overview/what- is-kubernetes/, accessed in Jan. 2021.

[26]   Jay Shah and D. Dubaria (2019). Building Modern Clouds: Using Docker, Kubernetes Google Cloud Platform, IEEE 9th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, USA, pp. 0184–0189.

[27]   Air Quality Data, in https://data.gov.in, accessed in Nov 2020.

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