

PANDA: Preference-based Bandwidth Allocation in Fog-enabled Internet of Underground-Mine Things

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Abstract—Traditionally, sensor networks are surmised to enhance safety in underground mines by providing consistent monitoring of the conditions. However, to cope with the frequent condition changes of such a hostile environment, we need a specific network architecture for the deployed nodes to enable dynamic decision making. In this paper, we argue that the fog computing paradigm can be leveraged to ensure safety in the Internet of Underground-Mine Things. We emphasize on prioritizing and speeding up the processing of sensitive data by introducing a factor named ‘criticality index’ and ensuring the fairness of bandwidth allocation using this index to comply to the resource requirement of critical data. We formulate the interaction between the fog nodes using the notions of the Stackelberg game. Simulation-based results show that using the proposed scheme, the fog nodes are able to allocate bandwidth with less average error and offset bandwidth, compared to the benchmark schemes.

Index Terms—Fog computing, Stackelberg game, mines safety, data-criticality

I. INTRODUCTION

Mining is one of the critical industry sectors. In particular, the underground mine is an environment where different hazardous gases are released during the process of coal extraction, roof fall and side fall are frequent, and mine fire is obvious. According to the reports of NIOSH, there were 26 mining fatalities reported in the year 2015 in US [1]. The extreme environment of mines urges for a technological system that can continuously monitor the events, safety conditions, and different accidental situations in the mines and can take immediate actions in case of any discrepancies.

Internet of Things (IoT) is a prominent technology that interconnects different devices and provides real-time monitoring service. Therefore, IoT finds its major applications in the industrial sector symbolizing itself as the Industrial Internet of Things (IIoT) [2]. This feature of IIoT makes it suitable for monitoring the conditions of mines and leverage safety to the mine workers by forming a network system named Internet of Underground-Mine Things (IoMT). However, cloud-based IoMT suffers from the problem of high delay, the enormous volume of data, and the high bandwidth requirement for the bulk data to transit to the cloud [3]. Consequently, these reasons hinder the real-time services of the system, which may result in severe accidents for sensitive applications like underground mines [4].

Fog computing emerges as a solution to the problems of the cloud by bringing the services near the edge and thus, minimizing the service latency [3]. The fog nodes process some of the data at the fog layer itself, which speeds up the response and also minimizes the volume of data at cloud [5]. The overall features of fog computing provide a pathway for enhancing the safety of mines with the incorporation of fog computing in the IoMT system. Recent literature [6] describes the effectiveness of fog computing in the systems where immediate action is necessary on some critical data like healthcare [7] and underground mines [8], which may prevent serious accidents.

The sensitive environment of the underground mines requires the data to be served with minimal delay. Existing works in the literature [9]–[11] focused on the need of real-time service in the underground mines and proposed methods like the introduction of the wireless sensor network (WSN) and IoT to achieve it but failed to address on how to minimize the latency of processing of data. Moreover, fog computing is the most suitable technology for these kinds of latency-sensitive IoMT environments where the data requiring immediate actions can be processed at the edge. Since the fog nodes are limited in resources, the entire data from the terminal layer cannot be processed at the fog layer. This demands the data to be filtered according to its delay requirement so that the fog nodes can decide what data to be sent to the cloud and what to be processed at the fog layer.

Besides, the prioritized data should be taken care of that its processing does not get delayed due to the scarcity of resources or some network hurdles. One such hurdle is the bandwidth requirement. The presence of limited bandwidth for underground mines requires its efficient usage so that the need for criticality-based data categorization is satisfied. For example, critical data needs to be transitted faster for its immediate processing and hence, require a high data rate. Therefore, the implementation of fog computing inside the underground mines raises questions such as *what data is to be processed at the fog layer, how to prioritize the data, how to fulfill the resource requirement of the prioritized data.*

To design a complete system that can offer a real-time service along with categorizing the data and fulfilling the demands of categorized data is itself a challenging task for various reasons – the extreme labyrinths of underground mines, the dynamic and adverse environment that changes with time, and limited resources of the devices serving the objective. Since the environmental conditions change with time, the system should be able to fulfill the dynamic resource demand of the fog nodes. Meanwhile, the system should be

able to cope with the sensitivity of the data with limited resource, while keeping the latency of processing and response minimal.

A. Contributions

To address the issues with the cloud-based IoMT architecture, we propose a hierarchical fog computing based architecture for the underground mines along with an algorithm, termed as, **P**reference **b**AseD **b**A N dwiDth **A**llocation (PANDA), for allocating bandwidth to the fog nodes located in each zone of the underground mine. In particular, the major *contributions* of this work are:

- We propose a fog computing-based architecture specific to underground mines to enhance real-time safety in the mine environment by prioritizing the data based on its criticality.
- We introduce a factor called *criticality index* to categorize the data to be processed at the fog nodes based on the severity of the zone determined from the environmental data for efficient utilization of fog resources.
- We model the interaction between the fog nodes using the Stackelberg game [12] to enable the dynamic allocation of bandwidth to the fog nodes according to the change in the environment of the deployment scenario based on their criticality.

II. RELATED WORKS

In this section, we present the prior works towards safety provisioning in underground mines. With the rapid increase in the application of WSN in different domains, several approaches are proposed to achieve safety in underground mines using WSNs [10] [9]. Moridi *et al.* [10] described a GIS integrated WSN system for controlling and monitoring underground mines activity remotely. Similarly, Minhas *et al.* [9] proposed a system in which they mainly focused on the design issue of the network in the mines and proposed an attribute and spatio-temporal correlated event detection algorithm. However, the authors did not consider the processing of data based on the criticality and consider the same priority for all the data which is not feasible in the mine environment.

To handle the huge amount of data produced by WSNs in the underground mines, authors in literature [13], [14] introduced IoT-based systems for underground mines. Jo and Khan [13] discussed a platform for monitoring, analyzing, and locating the miners using IoT. A cluster tree-based Zigbee network was proposed by Cheng *et al.* [14] for the access and distribution of sensory data using OSGI-mechanism and publisher-subscriber mechanism, respectively. The mashup networks mainly focus on information services and physical device integration. All the mentioned work discussed the processing of data at the cloud, which increases the delay for the data.

To focus on the efficient utilization of resources, different bandwidth allocation strategies have been discussed in the literature [15], [16]. A bandwidth allocation model is discussed by Jang *et al.* [15] in their work for the software-defined network (SDN)-based smart homes. They aimed at

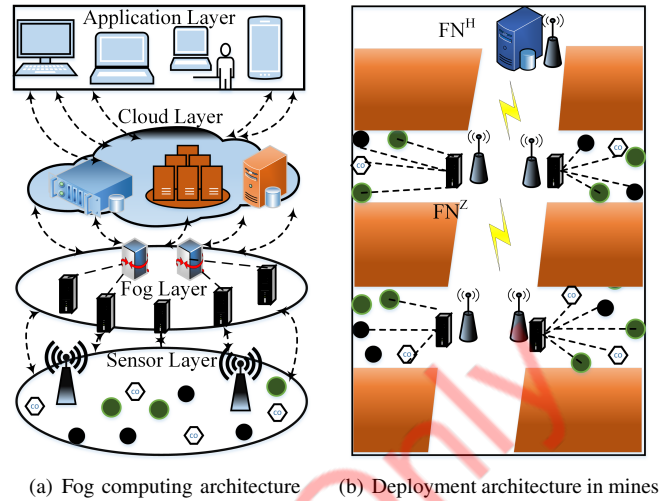


Fig. 1: Fog computing architecture for Underground Mines

improving the QoS and preventing resource starvation. Wang *et al.* [16] presented the bandwidth allocation scheme in M2M communication, where they allocated the bandwidth based on the signal-to-noise ratio (SNR) of the links to the access points (APs). Nevertheless, the works do not consider the allocation for prioritizing the critical data.

Game theory has been widely used in the literature [17]–[20] for proper management of resources. Barabadi *et al.* [17] presented a game between the consumers of the smart grid for sharing the load by increasing user participation. Feng *et al.* [18] introduced a game-based model in fog computing for improving the security of the system, while handling the cyber risks. To handle the computation-intensive tasks, a resource sharing scheme based on stackelberg game is proposed by Du *et al.* [19]. Mansouri *et al.* [20] presented a computation offloading game model to optimally allocate the fog resources among the IoT users. The aforementioned works assure the efficiency of game model in efficient resource allocation.

Synthesis: It is noticeable that underground mine application requires immediate actions on critical data of different zones. An intense study of the existing works unveils that none of the works have considered the delay in processing the data at the cloud or base station, which may result in serious hazards. Additionally, the bandwidth requirement for transmitting the data of different zones to the cloud may differ according to the criticality of zones. This introduces a need for an efficient algorithm that can overcome the stated problem.

III. SYSTEM MODEL

We consider the scenario of a tunnel-shaped underground coal mine having various branches, namely, *zones* and a four-layer IoMT fog architecture consisting of user/application layer, cloud layer, fog layer, and sensor/end devices layer as shown in Fig. 1. The bottom-most layer of the IoMT architecture consists of the terminal layer comprising the sensor nodes in the zones and the middle layer is the fog layer consisting of fog devices. The third layer is the cloud layer, and lastly, the application layer, where the services are

TABLE I: List of Notations

| Symbols | Definitions | Symbols | Definitions |
|---------------------|---|----------------------|--|
| N | Total number of ZFNs/zones in underground mine | L | Number of iterations of the proposed game model |
| \mathcal{FN}^z | ZFN in j^{th} zone | \mathcal{FN}^H | MFN |
| \mathcal{FN}^z | Set of ZFNs | \mathcal{CI} | Criticality index |
| $B_{p,k}$ | Purchased bandwidth at the k^{th} iteration | B_a^k | Bandwidth allocated at the k^{th} iteration |
| $B_{a,j}^k$ | Bandwidth allocated to j^{th} ZFN at the k^{th} iteration | DB_j | Desired bandwidth of J^{th} ZFN |
| $\Delta_{b_j}^k$ | Offset bandwidth of j^{th} zonal fog node at the k^{th} stage | $\lambda_{i,\tau}^j$ | Range of values of \mathcal{CI} for each ZFN |
| $\gamma_{h,\tau}^j$ | Maximum value of \mathcal{CI} for each ZFN | $\gamma_{l,\tau}^j$ | Minimum value of \mathcal{CI} for each ZFN |
| $d_{f,j}$ | Distance of each of the ZFN from the face of mine | d_{max} | Maximum distance between the starting end and face of mine |
| U_L | Utility function of Leader | U_{Fj} | Utility function of the j^{th} Follower |
| B_{aM} | Maximum allocated bandwidth | B_{am} | Minimum allocated bandwidth |
| B_{pM} | Maximum purchased bandwidth | B_{pm} | Minimum purchased bandwidth |
| O_k | Offset bandwidth of all the followers | E_k | Average error of leader |
| $AQDI$ | Air Quality Depreciation Index | HI | Heat Index |

accessed. Notably, in an IoMT, we categorize the fog nodes in two classes, namely, *master fog node (MFN)* and *zonal fog node (ZFN)* such that the former one has more computing and processing capability (in terms of CPU frequency, storage, and energy) in comparison to the latter one. As the name suggests, ZFNs are located in each zone of the underground mine, whereas the MFN is situated at the starting end of the tunnel. Let, there are N number of fog nodes known as *zonal fog nodes (ZFNs)*, each deployed in different zones and one *master fog node (MFN)* is located at the starting end of the tunnel as shown in Fig. 1(b). We represent the set of ZFNs as $\mathcal{FN}^z = \{f_1, f_2, \dots, f_N\}$ and MFN by \mathcal{FN}^H . The data from different sensors of each zone is transmitted to the respective ZFNs i.e. $\mathcal{FN}^z_j, \forall j \in [1, N]$. The ZFNs perform the data preprocessing and handle the more critical data by itself after calculating the criticality. Otherwise, the ZFNs forward the data to the MFN. It is noteworthy that ZFNs are less powerful than MFN and hence, the decision of processing the data at ZFNs depends on their resources, computation capability, and sensitivity of the data.

Definition 1. The Bandwidth allocated (B_a^k) by the MFN is defined as the sum of the individual bandwidth allocated to each of the ZFN ($B_{a,j}^k$) in the k^{th} iteration. Mathematically,

$$B_a^k = \sum_{j=1}^N (B_{a,j}^k) \quad (1)$$

Definition 2. The Criticality Index (\mathcal{CI}) of a ZFN is the parameter that determines the criticality of data received from sensors or end devices in that specific zone. Mathematically, \mathcal{CI}_j for j^{th} ZFN is defined as:

$$\mathcal{CI}_j = \left\{ k_1 \times \frac{(HI - HI_{Lo})}{HI_{Hi} - HI_{Lo}} \right\} - \left\{ k_2 \times \frac{AQDI}{10} \right\} \quad (2)$$

where HI is the heat index and $AQDI$ is the air quality depreciation index.

Definition 3. Desired bandwidth (DB_j) of j^{th} ZFN is defined as the product of the $B_{p,k}$ and \mathcal{CI} of j^{th} ZFN (\mathcal{CI}_j). Mathematically,

$$DB_j = B_{p,k} \times \mathcal{CI}_j \quad (3)$$

where $B_{p,k}$ and \mathcal{CI}_j denote the purchased bandwidth of MFN and the \mathcal{CI} of j^{th} ZFN, respectively.

Definition 4. Offset bandwidth (Δ_{b_j}) of j^{th} ZFN is defined as the difference between the desired bandwidth of j^{th} ZFN and the bandwidth allocated by the MFN to j^{th} ZFN. Mathematically,

$$\Delta_{b_j}^k = DB_j - B_{a,j}^k \quad (4)$$

where DB_j and $B_{a,j}^k$ is the desired bandwidth and allocated bandwidth of j^{th} ZFN in the k^{th} iteration, respectively.

Definition 5. The preference list is a list of values which reflect the historical background related to the criticality of data and the bandwidth allocated to each of the ZFNs. It is used for allocation of bandwidth to each of the ZFNs arranged in the order of their preference, and is maintained and updated by MFN as:

$$B_{a,j}^k = B_{a,j}^{k-1} \pm \Delta_{b_j}^k \quad (5)$$

where the following condition – Equation (6) and (7) holds.

$$\sum_{j=1}^N (B_{a,j}^k) \leq B_{p,k} \quad \forall k \in [1, L] \quad (6)$$

$$B_{a,j}^1 = \frac{B_{p,k}}{N} \quad \forall j \in [1, N] \quad (7)$$

Here, L represents the number of iterations in the game, $\Delta_{b_j}^k$ is the offset bandwidth, $B_{a,j}^k$ and $B_{a,j}^{k-1}$ are the allocated bandwidth of j^{th} ZFN in the k^{th} and the $(k-1)^{th}$ iteration, respectively, $B_{p,k}$ is the purchased bandwidth in the k^{th} iteration and $B_{a,j}^1$ is the bandwidth allocated to the j^{th} ZFN initially.

IV. PROPOSED MODEL

A. Problem Description

Since the bandwidth purchased by the MFN is limited, it needs to allocate the bandwidth to the ZFNs efficiently, while fulfilling their demands. Moreover, the demands of ZFNs vary with their computed \mathcal{CI} based on the change in the environment. To ensure the minimum delay for critical data by optimally allocating bandwidth to ZFN by MFN, we formulate the problem using a single-leader multi-follower Stackelberg game. In PANDA, ZFNs compete to attain their desired bandwidth from the MFN. Stackelberg game allows the MFN to adopt a strategy for optimizing the bandwidth allocation, while ensuring that the ZFNs adopt the strategy to minimize the offset bandwidth according to their criticality. The MFN allocates

the bandwidth to the ZFNs based on the preference list, which is then updated according to the Δ_{bj}^k submitted by the ZFNs. In the proposed game, FN^H is the leader, $\{FN_j^z\}_{j \in [1, N]}$ are the set of followers. $S_L = \{B_{p,1}, B_{p,2}, \dots, B_{p,L}\}$ and $S_{Fj} = \{\Delta_{(bj,1)}^k, \Delta_{(bj,2)}^k, \dots, \Delta_{(bj,L)}^k\}, \forall j \in [1, N]$ denote the strategy sets of the leader and the j^{th} follower, respectively.

B. Utility Functions

In the proposed game, we define a function that is used to assign a number to a particular strategy of player (leader or follower) depending on the strategy taken by them. The most preferred strategy is indicated by the higher value of the utility function.

1) *Utility Function of the Leader (U_L):* The strategy of the leader is to optimally allocate its purchased bandwidth, which depends on the maximum bandwidth purchased by the leader in any iteration denoted as B_{pM} and the minimum allocated bandwidth as B_{am} . Consequently, the utility function of the leader depends on:

- i. The difference between the bandwidth purchased ($B_{p,k}$) in the k^{th} iteration and the bandwidth allocated (B_a^k) to all of the followers, defined as: $\frac{\delta U_L}{\delta(B_{p,k} - B_a^k)} < 0$
- ii. The difference between current and previous allocated bandwidth ($B_a^k - B_a^{k-1}$), where k denotes the number of iterations involved in the game, is given by: $\frac{\delta U_L}{\delta(B_a^k - B_a^{k-1})} < 0$

Therefore, considering the above dependencies along with the maximum purchased and the minimum allocated bandwidth, we present the utility function of the leader as,

$$U_L = \frac{B_{pM} - B_{am}}{B_{p,k} - B_a^k} \times \frac{B_{am} - B_{am}}{|B_a^k - B_a^{k-1}|} \quad \forall k \in [1, L] \quad (8)$$

2) *Utility Function of the Follower ($U_{Fj}, \forall j \in [1, N]$):*

The objective of the follower is to adopt a strategy that will optimize its offset bandwidth which depends on CI. Therefore, the utility of each of the followers while considering the minimum bandwidth allocated to each follower as $B_{am,j}$ depends on the following factors:

- i. The Offset Bandwidth ($\Delta_{bj}^k, \forall j \in [1, N]$) of the follower, defined as: $\frac{\delta U_{Fj}}{\delta(\Delta_{bj}^k)} < 0$
- ii. The Criticality index (CI) of the follower, defined mathematically as: $\frac{\delta U_{Fj}}{\delta CI_j} > 0$

Therefore, based on the above dependencies, we formulate the overall utility function of follower as:

$$U_{Fj} = \frac{b \times CI_j \times (DB_{max,j} - B_{am,j})}{\Delta_{bj}^k} \quad (9)$$

where, $DB_{max,j} = \gamma_{h,\tau}^r \times B_{p,k}$. $DB_{max,j}$ is the maximum desired bandwidth of the j^{th} ZFN and $b \in \{-1, 1\}$ takes care of the sign of the utility function so that it is always positive.

C. Objective of the Leader

The objective of the leader is to maximize its utility by purchasing the optimal amount of bandwidth which will be sufficient for the requirement of all followers. To achieve

this, the leader keeps on updating the preference list in every iteration based on the information provided by each of the followers. Therefore, the objective of the leader is subject to the constraint that the purchased bandwidth should satisfy the needs of the ZFNs, while not exceeding the maximum purchased bandwidth in any iteration. Mathematically, it can be stated as:

$$\begin{aligned} \max \quad & U_L \\ \text{s.t.} \quad & B_{p,k} \geq \sum_{j=1}^N DB_j; \quad \forall k \in [1, L] \\ & B_{p,k} \leq B_{pM}; \quad \forall k \in [1, L] \end{aligned} \quad (10)$$

D. Objective of the Follower

Due to the lack of sufficient computational resources, ZFNs cannot process all the data and at the same time cannot risk the delayed processing as well. Thus, the objective of the followers is to instantly transmit the data to the leader as soon as they receive it from the sensors deployed in their respective zones. To achieve this objective, the followers need sufficient bandwidth allocated by the leader, which could help in transmitting the data to the leader at low energy consumption and delay, thereby maximizing their utilities. However, this objective is subject to the constraint that the minimum allocated bandwidth should be at most the desired bandwidth, while keeping the offset bandwidth lower than the difference between the desired and the minimum allocated bandwidth. We formulate this as:

$$\begin{aligned} \max \quad & U_{Fj} \\ \text{s.t.} \quad & DB_j \geq B_{am,j}; \quad \forall j \in [1, N] \\ & \Delta_{bj}^k \leq (DB_j - B_{am,j}); \quad \forall j \in [1, N] \end{aligned} \quad (11)$$

Theorem 1. *There exist a Nash-Cournot equilibrium for our proposed Stackelberg game-based model, which is stated as:*

$$U_L(s_L, s_{-L}) \geq U_L(\bar{s}_L, s_{-L}) \quad \forall \bar{s}_L \in S_L. \quad (12)$$

Here, we consider that $s_L = ((B_{p,k} - B_a^k), |B_a^k - B_a^{k-1}|)$ is the strategy pair of the leader in the k^{th} iteration, whereas $\bar{s}_L = ((\bar{B}_{p,k} - \bar{B}_a^k), |\bar{B}_a^k - \bar{B}_a^{k-1}|)$ is the strategy of the leader in other iterations. We denote the strategy profile of the followers as s_{-L}

$$U_{Fj}(s_{Fj}, s_{-Fj}) \geq U_{Fj}(\bar{s}_{Fj}, s_{-Fj}) \quad \forall \bar{s}_{Fj} \in S_{Fj}, \forall j \in [1, N] \quad (13)$$

where, $s_{Fj} = (CI_j, \Delta_{bj}^k)$ is the strategy of j^{th} follower in the k^{th} iteration, whereas $\bar{s}_{Fj} = (CI_j, \bar{\Delta}_{bj}^k)$ is the strategy pair of the j^{th} follower in other iterations. Here, s_{-Fj} is the strategy profile of other followers including leader.

Proof. This can be proved by varying the strategy of leader and follower keeping the s_{-L} and s_{-Fj} fixed, respectively. \square

Theorem 2. *There exist a zero conjectural variation in our proposed Stackelberg game model.*

Proof. The theorem can be proved by taking the contradiction that the choice of DB_j depends on others strategy. \square

Theorem 3. *The difference between the purchased bandwidth and the bandwidth allocated converges, i.e.,*

$$B_{p,k} - B_a^k = 0 \quad \forall k \in [1, L] \quad (14)$$

Proof. This can be proved using mathematical induction on k . \square

Theorem 4. *The offset bandwidth of ZFNs (O_k) is minimized using Stackelberg game as compared to the case when no game model is used i.e.,*

$$O_k < O'_k$$

where, O'_k is the offset bandwidth of ZFNs when no game model is used.

Proof. This can be proved by contradiction. \square

E. PANDA: Proposed Scheme

In PANDA, MFN allocates its purchased bandwidth to the ZFNs. ZFNs compute the CI of their zone and evaluate the Δ_{bj}^k . The Δ_{bj}^k is informed back to the MFN by the ZFNs. MFN then updates its preference list and allocates the bandwidth accordingly in the next iteration. The objective is to minimize the value of Δ_{bj}^k . To maximize the respective utilities, MFN and ZFN follow Algorithm 1 and Algorithm 2, respectively.

1) *Algorithm for the Leader:* Let $B_{p,k}$ be the purchased bandwidth. Suppose the leader allocates $B_{a,1}^k, \dots, B_{a,j}^k, \dots, B_{a,N}^k$ bandwidth to each of the N followers in the k^{th} iteration based on the preference list. Let $DB_1, \dots, DB_j, \dots, DB_N$ denote the desired bandwidth of the ZFNs. The strategy followed by the leader to maximize its utility is to update the preference list in each iteration according to Δ_{bj}^k information. The update in the the preference list for each of the followers at the $(k+1)^{th}$ iteration takes place as discussed in the following.

Considering the j^{th} follower, if $DB_j > B_j$ i.e. $\Delta_{bj}^k > 0$ or if $DB_j < B_j$ i.e. $\Delta_{bj}^k < 0$ then $B_{a,j}^{k+1} = B_{a,j}^k + \Delta_{bj}^k$. The proposed algorithm for the MFN is presented in Algorithm 1.

Algorithm 1: Algorithm for leader

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1 Inputs:  $B_{p,k}, B_a^k, CI, \Delta_{bj}^k$ .
2 Output: Preference list.
3 for  $k \in [1, L]$  do
4   for  $j \in [1, N]$  do
5     Allocate the bandwidth to  $j^{th}$  ZFN based on
       preference list;
6     Wait for the  $j^{th}$  ZFN to inform about  $\Delta_{bj}^k$ ;
7     if  $(\Delta_{bj}^k > 0 \text{ or } \Delta_{bj}^k < 0)$  then
8       Leader updates the preference list as shown
       in Equation (5);
9     else
10      No updation in the preference list;

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2) *Algorithm for the Follower:* To maximize the utility, the follower's strategy is to minimize the offset bandwidth. To attain this, in each iteration, after the bandwidth is allocated to each of the ZFNs (followers) by the MFN (leader), the ZFN computes its desired bandwidth using the value of CI and Δ_{bj}^k according to the Equation (3) and Equation (4). If the value of Δ_{bj}^k for the j^{th} follower results in non-zero value then the follower can choose the desired bandwidth based on the range of CI such that the offset bandwidth is minimum. Then, the MFN is informed and it takes necessary actions accordingly. Otherwise, the leader is not informed when the value of Δ_{bj}^k evaluates to zero.

Algorithm 2: Algorithm for follower

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1 Inputs:  $CI, DB_j, B_{a,j}^k$ .
2 Output:  $\Delta_{bj}^k$ .
3 for  $k \in [1, L]$  do
4   Each follower is allocated the bandwidth( $B_{a,j}^k$ ) by
       the leader;
5   for  $j \in [1, N]$  do
6     Calculate the value of  $DB_j$ ;
7     Compute the value of offset bandwidth ( $\Delta_{bj}^k$ );
8     if  $\Delta_{bj}^k \neq 0$  then
9       Choose the value of  $DB_j$  based on the
       range of  $CI$  such that  $\Delta_{bj}^k$  is minimum;
10      Send the value of  $\Delta_{bj}^k$  to the leader;
11    else
12      Do not inform to the leader;

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V. PERFORMANCE EVALUATION

A. Simulation Settings

For evaluating the performance of our proposed model, we vary the number of zones (N) and compare the different performance metrics for different variations in CI . The experiments in the simulations are repeated for 100 number of iterations and are averaged to plot the results. We consider that the leader purchases bandwidth within the range of 840 – 850MHz such that the frequencies present in the purchased bandwidth lies in the ISM band. The bandwidth is allocated to all the followers in a way so that each of the followers receives the bandwidth within the range of 30 – 80MHz.

1) *Different types of variation in CI and justification for such choice:* We vary the criticality of different zones in the range [0.01, 0.06] by varying the value of CI which depends on the different conditions of the mines. For example, in India, the underground mines are categorized according to the gassiness in the mines as *degree 1*, *degree 2*, and *degree 3* [21]. The zones where the current coal excavation is being carried out are more prone to danger than the zones from which the excavation process is already finished. The environmental parameters also change according to these conditions and hence, the criticality varies. Thus, we formulated the criticality

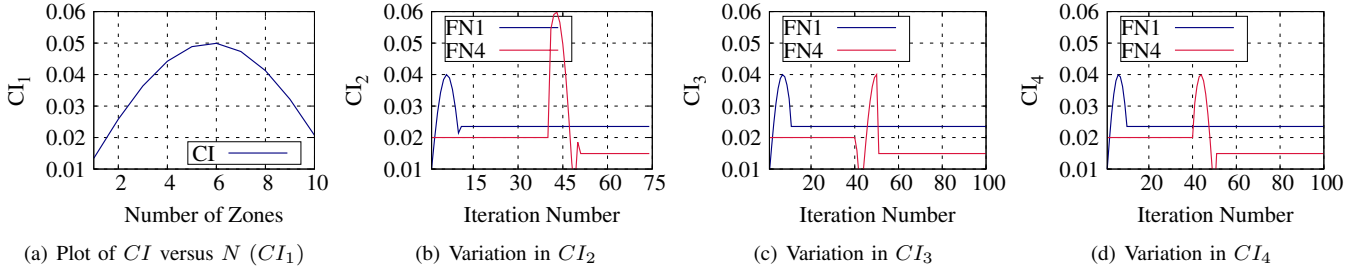


Fig. 2: Different types of variation in CI

index to take care of the flashpoint of the zones in the underground mines.

The *second* case, CI_2 , shows a situation, where only one of the zones is under the critical condition at any point of time. Also, the range of criticality is different in different zones. This is simulated as – the value of CI for any particular zone increases gradually and it remains constant for other zones. This case is shown in Fig. 2(b) with CI variations of zone 1 and 4 (FN1 and FN4 respectively). Similarly, in the *third* case, CI_3 , we consider the situation where the criticality of the zone exists for different duration of time. The variations in CI in CI_3 is depicted in fig 2(c). Lastly, in CI_4 shown in Fig.2(d), we depict a situation where for a certain duration of time, the value of CI for a particular zone varies and remains constant for other zones.

B. Performance Metrics

The performance of the proposed scheme is evaluated with respect to the following metrics.

a) *Average error of the leader (E_k)*: Leader's average error is defined as the normalized value of the difference between $B_{p,k}$ and B_a^k in the k^{th} iteration of the game model. This metric helps in evaluating the efficiency of the leader's (MFN's) allocation of the available bandwidth among the followers (ZFNs). Mathematically, $E_k = \frac{B_{p,k} - B_a^k}{B_{pM} - B_{am}}$, $\forall k \in [1, L]$, where B_{pM} and B_{am} is the maximum and minimum value of $B_{p,k}$ and B_a^k , respectively.

b) *Offset bandwidth of the followers (O_k)*: It is defined as the sum of the offset bandwidth of all the followers in each iteration. Using this metric, we can show the effectiveness of the allocation of bandwidth from the followers' (ZFNs) perspective. Mathematically,

$$O_k = \sum_{j=1}^N (\Delta_{bj}^k) \quad \forall k \in [1, L] \quad (15)$$

c) *Time of convergence (τ)*: Time of convergence is the absolute value of the difference between iteration numbers of the maximum and the minimum value of the average error of the leader for every k/z iterations, where k is the iteration number and z represents the number of zones. This metric reflects the time taken to achieve the allocation.

C. Benchmark

To analyze the performance of *PANDA*, we compare it with an existing scheme weighted – delay-based bandwidth

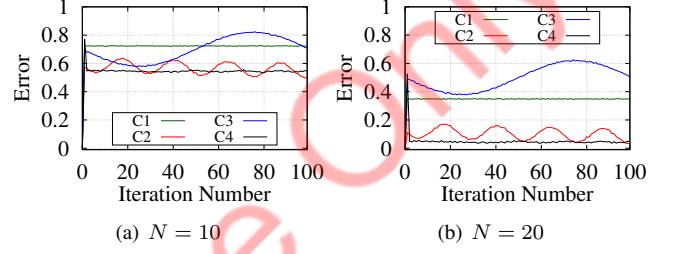


Fig. 3: Average error of leader for different CI using proposed scheme

allocation in SDN (*SDN*) [15] and different bandwidth allocation approaches – *EQUAL* and *RANDOM*. In delay-based allocation, the data is categorized based on the delay requirement. Since the game model allows dynamic allocation of bandwidth based on criticality, the comparison with *SDN* will show the effectiveness of *PANDA* in mines. The other benchmark scheme used for comparison is *EQUAL*, where the purchased bandwidth is allocated equally among the followers in every iteration, irrespective of the knowledge about the desired bandwidth of each of the followers. Further, in *RANDOM*, as the name suggests, the purchased bandwidth is allocated randomly to each of the followers by the leader in every iteration. In the benchmark schemes, the bandwidth is allocated without considering the changes in the deployment environment. In contrast, we leverage the information from the ZFNs to aid the bandwidth allocation process in the proposed scheme *PANDA*. Due to this reason, we use *EQUAL* and *RANDOM* as benchmarks.

D. Results and Discussions

Fig. 3 shows the variation of the E_k with the number of iteration numbers for different types of variation of CI when the number of zones is equal to 10 and 20. E_k decreases with the increase in the number of zones in *PANDA* for all types of variation of CI . Thus, it is evident that *PANDA* achieves a better result for E_k when there is more number of zones in the underground mine.

1) *Average Error of the Leader*: Fig. 4 shows the comparison of E_k for each of the schemes for CI_2 . Figs. 4(a)-4(b) shows that E_k is zero for *EQUAL*, whereas it is non-zero for *RANDOM*, *SDN*, and *PANDA*. This is because the purchased bandwidth in *EQUAL* is divided equally among the ZFNs,

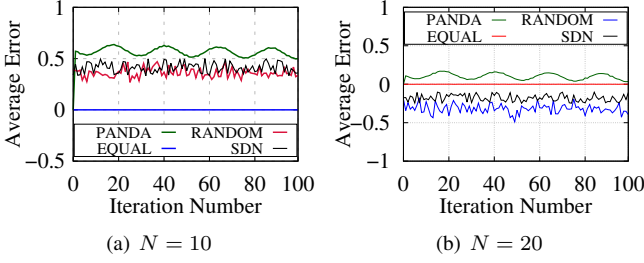


Fig. 4: Comparison of average error of leader for different schemes

and thus, E_k is always be zero, whereas, in all the other three schemes, this difference always varies. In *RANDOM* the error varies due to the randomness in the allocation which results in different values of the error, while the variation in *SDN* is observed due to its fixed bandwidth allocation based on delay. In contrast, although E_k is slightly higher in *PANDA*, the fluctuation of the error is less compared to the benchmarks. Also, it is evident from the results that E_k computed using *PANDA* decreases with the increase in the number of zones as shown in Figs. 4(a) and 4(b). Therefore, *PANDA* is scalable with the number of zones in the underground mine.

2) *Offset Bandwidth of the Followers*: Fig. 5 shows the variation of the O_k for different types of variation in *CI* when the number of zones is varied. We compare the O_k by varying the number of zones which is shown in Figs. 5(a) and 5(b). It is evident from the results that as the number of zones is increased, O_k also increases slightly. This is due to the fact that with the increase in the number of zones, on an average, the probability of more number of zones receiving unsatisfactory bandwidth (the error of allocation may vary) increases.

Fig. 6 presents the comparison of O_k of followers evaluated using *PANDA* with that of *EQUAL*, *RANDOM*, and *SDN* for CI_2 , when the number of zones are varied between 10-20. From Figs. 6(a) and 6(b), it is observed that O_k in *PANDA* doesn't vary much and remains close to zero, whereas there are much deviation and variation in *EQUAL*, *RANDOM*, and *SDN* even when the number of zones are varied. *PANDA* performs better due to its game theoretic interaction model between leader and follower which ensures that the followers receive bandwidth close to their desired bandwidth. However, *EQUAL* and *RANDOM* do not consider the demands of ZFNs whereas *SDN* excepts the dynamic behaviour of ZFNs due to change in environment. Thus, *PANDA* excels all the other schemes.

3) *Time of Convergence*: Fig. 7 presents the variation of the time of convergence of error for different types of variation in *CI* when the number of zones is varied. It is evident from Figs. 7(a) and 7(b) that as the number of zones are increased from 10 to 20, it requires higher time to converge, for different variation in *CI*. This is because as the number of zones is increased, the probability of unsatisfactory bandwidth allocation to the followers also increases. Thus, the players of the game need more number of interactions to reach closer towards the desired values.

The convergence time (τ) of error for *PANDA*, *EQUAL*, *RANDOM*, and *SDN* considering CI_2 type of variation of

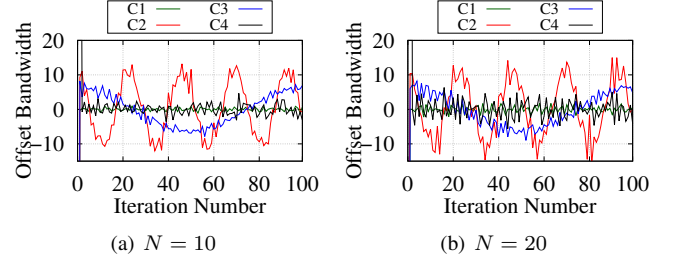


Fig. 5: Offset bandwidth of followers for different *CI* using proposed scheme

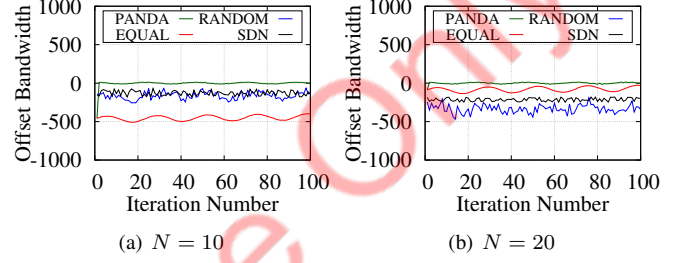


Fig. 6: Comparison of offset bandwidth of followers for different schemes

CI is shown in Fig. 8, when the number of zones are varied. It is evident from the figure that the τ of error is higher in *PANDA* than *EQUAL*, *RANDOM*, and *SDN*. Also, it increases with the increase in the number of zones due to more number of interactions between the leader and the follower in *PANDA*. The game model in *PANDA* induces this trade-off, which is lesser in other schemes. In contrast, *EQUAL* outperforms the other schemes due to minimum average error, while *SDN* performs better than *RANDOM* for its delay-based fixed allocation of bandwidth and tends to be correct until the environment changes. Thus, *PANDA* induces more delay in converging the error than the other schemes.

VI. CONCLUSION

In this paper, we presented a novel fog computing-based architecture for IoMT framework and argued that this paradigm can be leveraged to ensure safety in the underground mine with appropriate bandwidth allocation to the fog nodes. We prioritized the processing of sensitive data of mines by proposing a scheme, *PANDA*, for fair allocation of bandwidth between

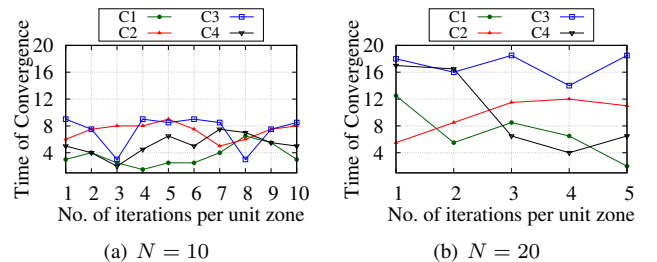


Fig. 7: Time of convergence of error for different *CI* using proposed scheme

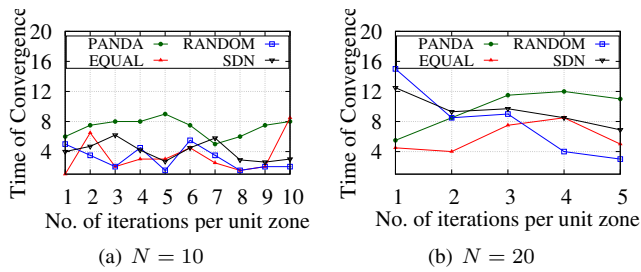


Fig. 8: Comparison of time of convergence of error for different schemes

the fog nodes based on the ‘criticality index’. The interaction between the fog nodes is formulated as a Single-Leader Multi-Follower Stackelberg game. Specifically, the paper studied two major problems of underground mines – real-time safety with immediate actions and prioritizing critical data using efficient bandwidth allocation. Simulation-based results depicted that PANDA reduced the bandwidth allocation error and offset bandwidth, thus, prioritizing critical data, and thereby enhancing safety. In the future extensions of the current work, we plan to implement the proposed scheme for experimenting in underground mines under different conditions.

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