DENSE: Dynamic Edge Node Selection for Safety-as-a-Service

Chandana Roy*, *Student Member, IEEE*, Sudip Misra†, *Senior Member, IEEE*, Jhareswar Maiti‡, *Member, IEEE*
Mohammad S. Obaidat$, *Fellow, IEEE*
*‡Department of Industrial and Systems Engineering, †Department of Computer Science and Engineering,
$School of Information Technology,
*†‡Indian Institute of Technology Kharagpur, India, $University of Jordan
Email: {*chandanaroy, †sudipm}@iitkgp.ac.in, ‡jmaiti@iem.iitkgp.ernet.in, $msobaidat@gmail.com

***Abstract*—In this paper, we propose a dynamic edge node selection scheme, named as DENSE, for the Safety-as-a-Service (Safe-aaS) architecture [1]. A Safe-aaS infrastructure provisions customized safety-related decisions remotely to the registered end-users. Depending on the time-criticality of data, the static and mobile sensor nodes sense and transmit data to the edge nodes. The number of edge nodes present within the proximity of a mobile sensor node vary with the change in the locations of the vehicle. Moreover, the distance between the mobile sensor node and the edge nodes, within its proximity, change with the variation in the vehicle's location. Therefore, in such a situation, dynamic selection of the appropriate edge node for processing the time-critical data is necessary. To optimally select the edge node, we use cooperative coalition-based game theoretic approach. Further, we apply *Karush-Kuhn-Tucker* (KKT) conditions to find the existence of equilibrium. The analytical results of our proposed scheme, DENSE, shows that the average utility increases by 11.33% with respect to the available storage space of the edge nodes. Moreover, the average utility increases by 50.43% with respect to the average number of tasks executed per unit time by the edge node.**

Keywords*—*Road transportation, Cooperative coalition game, Safety-as-a-Service, Edge nodes.

I. Introduction

The rapid rise in the number of on-road vehicles result in the upsurge of the road congestion, accidents, and casualties. However, the prior delivery of prompt and correct safety-related decisions lead to the improvement in the road safety conditions. On the other hand, the Internet of Things (IoT)-based technologies applicable in the industries (Industrial Internet of Things (IIoT)), enable automation and connectivity among the devices or things. Specifically, Internet of Vehicles (IoV), a sub-set of the IIoT-based technologies, are widely used in the road transportation industry to improve the safety of on-road vehicles and drivers. Additionally, the development of IoV-based technologies such as Intelligent Transportation System (ITS) [2] and Advanced Driver Assistance System (ADAS), reduce accidents and traffic jams.

The primary focus of this paper is to design a scheme for the dynamic selection of the edge nodes in a Safe-aaS architecture [1]. A Safe-aaS infrastructure provides customized safety-related virtualized decisions to the multiple registered end-users simultaneously. The end-users register to the Safe-aaS architecture through a Web portal and select certain decision parameters. Thereafter, the generated decisions are remotely delivered to the registered end-users. As depicted in Fig. 1(a), heterogeneous type of sensor nodes are present in the device layer of Safe-aaS which sense and transmit data to the edge layer or cloud, based on the time-criticality of data. The static sensor nodes are deployed at a fixed geographical location, therefore, the set of edge nodes present within the vicinity of the static sensor node does not vary. On the other hand, the location of mobile sensor nodes vary with the mobility of the vehicles as shown in the Fig. 1(b). Consequently, the number and type of neighboring edge devices of the mobile sensor nodes also changes. Further, in edge devices, the storage capacity and number of task execution capability vary, based on their type. Since any delay in processing the data is unacceptable in the Safe-aaS architecture, thus, dynamic selection of the appropriate edge device is necessary. We apply cooperative coalition-based game-theoretic approach to optimally select the edge node.

On-road safety of the vehicles and drivers is the primary aspect of concern of a Safe-aaS architecture. The Safe-aaS infrastructure is based on pay-per-use model, where the end-users pay for the customized safety-related decisions. The static and mobile sensor nodes sense and transmit the time-critical data to the edge layer for primary processing. Further, the geographical location of the mobile sensor nodes change with the mobility of the vehicles. Consequently, the neighboring edge nodes of the mobile sensor node also vary. On the other hand, based on the type of edge nodes, the storage space and task execution capability of the edge nodes vary from one another. As the data is time-critical in nature, any delay in processing may result in injury, congestion, and accident. Therefore, there is a requirement of dynamic selection of the appropriate edge node, which is capable of processing the time-critical data efficiently. We propose our scheme, DENSE, which utilize cooperative coalition-based game-theoretic approach to optimally select the neighboring edge node among the available ones.

In this work, we focus on the dynamic selection of edge nodes in road transportation for the processing of time-sensitive data. The specific *contributions* of this work are:

1) We propose a dynamic edge node selection scheme, DENSE. In order to select the appropriate neighboring edge node of any sensor node, we use cooperative coalitional game-theoretic approach, while considering the distance between the sensor node and the edge node, available storage space, average number of tasks executed per unit time, and reputation rating of the edge node.

2) In order to compute the equilibrium condition, we use a *Mixed-Integer Linear Programming* (MILP) approach. Further, we solve it using *Karush-Kuhn-Tucker* (KKT) conditions.
3) We perform an extensive simulation, which shows that the number of edge nodes present within the vicinity of any mobile sensor node, as well as the distance between the mobile sensor node and their neighboring edge nodes vary randomly with the mobility of the vehicle.

II. Related Work

In the recent years, different research works are explored in the domain of road transportation, which address the problems related to road congestion, accidents, and road safety. Uchimura *et al*. [3] designed a public transportation system, LINC, in order to provide door-to-door service to common people such as public taxi. The proposed system deliver services in three levels – regional community, inter-community, and within the community. Further, providing the safety-related informations in advance to vehicles and drivers, may reduce the possibility of accidents. In a recent work, Roy *et al*. [1] proposed a theoretical model, Safe-aaS, for the road transportation industry, which provides customized safety-related decisions remotely to the registered end-users. Moreover, the authors introduced the concept of *decision virtualization*, which enables a single decision to be shared among multiple end-users. In order to achieve high-speed and low-latency applications, sensors can be used for communication among vehicles to reduce traffic jams and air pollution. Tassi *et al*. [4] designed a mmWave-based highway communication network to influence the existing line-of-sight (LOS) models. The authors considered the heavy vehicles as blockages, with the assumption that the heavy vehicles drive only along the parallel lines. Further, the authors also assumed that the base stations are situated along the road-side. Considering the heterogeneous nature of the communication technologies available for vehicular networking, Cespedes *et al*. [5] proposed a hybrid global mobility scheme, which combine the host and network-based mobility in the urban vehicular scenarios. However, road safety is also a necessary component in the transportation system.

Considering the presence of edge and fog nodes in the IoT scenario, certain research problems are addressed. Mohan *et al*. [6] proposed an edge-fog cloud framework, which allocate the tasks for processing the available and participating cloud resources in the network. Based on the time required to process the tasks and network costs, the authors designed an algorithm to assign the task of devices. In another work, Gusev *et al*. [7] discussed the emergence of edge computing from the IoT perspective. Further, in order to reduce the real-time latency of edge networks, Hogan *et al*. [8] designed a path selection technique using portfolio theory. Additionally, the authors computed and compared the latency applying various error estimation techniques such as autoregressive model, moving average model, and autoregressive moving average (ARMA) model. Considering the maximum allowable work load and latency constraints, Ali *et al*. [9] proposed an optimization problem to jointly select the cloudlet and minimize latency in a fog network.

Synthesis: In the existing literatures, different research works explored various aspects of the road transportation industry. Considering the communication in the vehicular networks, Tassi *et al*. [4] and Cespedes *et al*. [5] proposed communication network for heavy vehicles and urban vehicles respectively. Further, in the Safe-aaS architecture [1], with the mobility of vehicles, the location of mobile sensor nodes change accordingly. In order to process the time-critical data, problem of dynamic selection of the appropriate edge device in the presence of heterogeneous sensor nodes and decision virtualization, is not yet addressed. The existing research works do not consider decision virtualization. Moreover, the type of edge nodes also differ from one another in terms of storage capacity and task execution capability. Hence, the dynamic selection of appropriate edge nodes is necessary. Therefore, we formulate the scheme, DENSE, for dynamic edge node selection in Safe-aaS architecture.

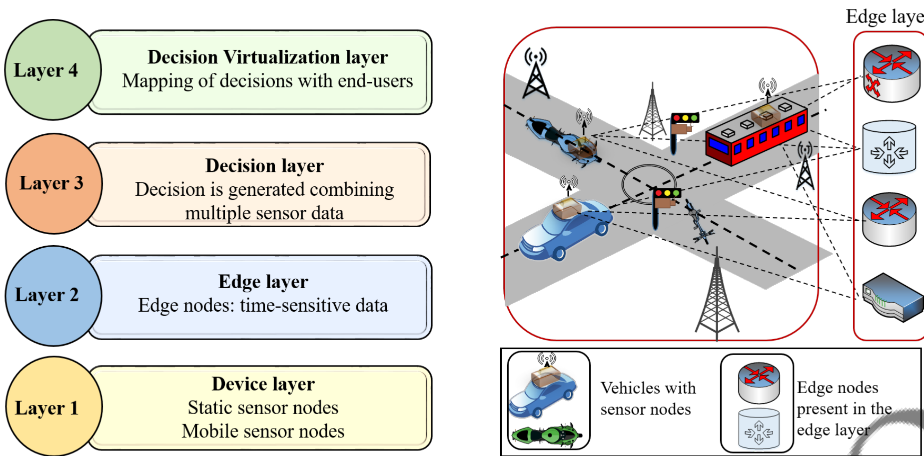
III. Problem Description

A. Problem Scenario

In this work, we consider a *Safe-aaS* architecture [1], applicable for the road transportation industry. There are four principal actors of the Safe-aaS infrastructure – vehicle owners, sensor owners, safety service provider (SSP), and end-users. The sensor nodes present in the device layer may be static or mobile in nature. Further, the sensor nodes deployed into the vehicles are considered as mobile, while those deployed at any particular geographical location are static in nature. Each sensor owner deploy heterogeneous sensor nodes over different geographical locations. Based on the type of vehicles owned by the vehicle owners, they are classified as – active and passive vehicle owner. Active vehicle owner has inbuilt sensor nodes in their vehicles. On the other hand, the other sensor owners may deploy sensor nodes into the vehicles of passive vehicle owners. Safe-aaS architecture comprise of four layers – *device layer*, *edge layer*, *decision layer*, and *decision virtualization layer*, as illustrated in Fig. 1(a). Heterogeneous physical sensor nodes are deployed at various geographical locations and vehicles in the device layer. These sensor nodes sense and transmit the data to the edge layer/cloud, based on the time-criticality of data. The primarily processed data are transmitted to the decision layer for generation of a decision. Further, multiple decisions are combined to generate a decision. The logical mapping between the end-users and the decisions generated are done in the decision virtualization layer. Fig. 1(b) shows the schematic view of the mobile and static sensor nodes, with the set of edge nodes. The storage capacity and average task execution capability is different for each type of edge node. Moreover, with the mobility of vehicles, the geographical location of a mobile sensor node changes. The number of edge nodes present within the communication range of the mobile sensor node is accordingly modified.

B. Problem Formulation

Let $\mathcal{S} = \{S_1, S_2, \cdots, S_m\}$ be the set of owners (including sensor and vehicle owner) present in the scenario. Each of the sensor owner deploy heterogeneous type of sensor nodes over different geographical locations or on the vehicles. Let, $\mathbb{S} = \{s_1, s_2, \cdots, s_n\}$ be the set of sensor nodes, which are either static or mobile in nature. Suppose, the number of static sensor nodes are represented by χ_{ij}^{s}. On the other hand, the number of mobile sensor nodes, belonging to active and passive vehicle owner, at the t^{th} time instant, are denoted as $\chi_{ij}^{m_a,t}$ and $\chi_{ij}^{m_p,t}$ respectively. Let, the different type of



(a) Layers of Safe-aaS

(b) Dynamic selection of edge node

Fig. 1: DENSE: The System Architecture

static and mobile sensor nodes belonging to the owner are represented by y_1 and y_2 respectively. The number of sensor owners, active and passive vehicle owners, present in the scenario are represented by x_1, x_2, and x_3, respectively. The total number of sensor nodes, $\mid \mathbb{S}_t \mid$, present in the scenario at any time instant, t, is mathematically represented in Equation (1).

$$\mid \mathbb{S}_t \mid = \sum_{j=1}^{x_1}\sum_{i=1}^{y_1}\chi_{ij}^{s} + \sum_{j=1}^{x_2}\sum_{i=1}^{y_2}\chi_{ij}^{m_a,t} + \sum_{j=1}^{x_3}\sum_{i=1}^{y_2}\chi_{ij}^{m_p,t} \quad (1)$$

The active sensor nodes sense and transmit the time-critical data to the edge nodes for primary processing. We consider $\mathcal{E} = \{E_1, E_2, \cdots, E_p\}$ as the set of edge nodes. The number of active sensor nodes at any time instant, t, be k, which is mathematically represented as:

$$\mathbb{S}_a = \{s_i : s_i \rightarrow (St \vee Mb) \mid \exists E_j \vee \psi(E_j)\} \quad (2)$$

where St and Mb represent the static and mobile sensor nodes. In Equation (2), E_j characterize the nearest edge node of the active sensor node, s_i. $\psi(E_j)$ denotes the function, which compute the set of edge nodes in the neighborhood of the sensor node, s_i. Any sensor node, s_i may be static or mobile in nature. The static type sensor nodes are activated mostly for continuous monitoring operation. On the contrary, the mobile sensor nodes are activated only when the vehicle is mobile, and their location varies with the mobility of the vehicle.

IV. Solution Approach

In a Safe-aaS architecture, the static and mobile sensor nodes sense and transmit data to the edge layer or cloud, based on the time-sensitivity of the data. The proposed scheme, DENSE, dynamically selects the appropriate neighboring edge node of the sensor node. The sensed data is primarily processed at the edge nodes. Thereafter, the primarily processed data are transmitted to the decision layer to generate a decision. The edge nodes are selected based on the following parameters:

Normalized distance (D_{ij}^N): The normalized distance between the sensor node and its neighboring edge nodes are computed using the *Euclidean distance* formula. We consider $\mathbb{A}_i = \{D_{i1}, D_{i2}, \cdots, D_{iq}\}$ as the set of distances between the i^{th} sensor node and the edge nodes within their proximity. Each D_{ij} represents the distance between the i^{th} sensor node to the j^{th} neighboring edge node. As shown in Equation 2, function $\psi(E_j)$ computes the set of neighboring edge nodes of any sensor node. Therefore, normalized distance is represented as:

$$D_{ij}^N = \frac{D_{ij}}{max(\mathbb{A}_i)} \quad (3)$$

where $max(\mathbb{A}_i)$ compute the maximum distance from the set $\mathbb{A}_i$.

Normalized available storage space ($\mathcal{AS}_j$): The normalized available storage space of the j^{th} edge node is the ratio of the remaining storage space, $\mathcal{AS}_j^r$, to the initial storage space, $\mathcal{AS}_j^{init}$, of the edge node. Mathematically:

$$\mathcal{AS}_j = \frac{\mathcal{AS}_j^r}{\mathcal{AS}_j^{init}} \quad \forall j, \quad j = \{1, 2, 3, \cdots, k\} \quad (4)$$

Similarly, we compute the $\mathcal{AS}$ for each neighboring edge node of the i^{th} sensor node.

Average number of tasks executed per unit time ($\mathcal{N}_j^{avg}$): We compute the average number of tasks executed per unit time of the j^{th} edge node using *Simple exponential smoothing method for time series forecasting* [10]. The average number of tasks initially executed by the edge node ($\mathbb{T}_\tau$), till time instant τ, is mathematically represented as:

$$\mathbb{T}_j^\tau = \frac{1}{\tau}\sum_{i=1}^{\tau} N_{ij} \quad (5)$$

where N_{ij} represents the number of tasks executed during the i^{th} time period by the j^{th} edge node. The forecast of the number of tasks (at the $(\tau+1)^{th}$ time instant) to be executed per unit time, $F_j^{\tau+1}$, is represented as $F_j^{\tau+1} = \mathbb{T}_j^\tau$. Therefore, the forecast of number of tasks to be executed after the initial time instant, F_j^1 will be equal to the average number of tasks initially executed, $\mathbb{T}_j^0$. After observing the number of tasks performed by the edge device in the $(t)^{th}$ time instant, the expected number of tasks executed till $(t)^{th}$ time period is mathematically expressed in Equation (6).

$$\mathbb{T}_j^t = \alpha \mathcal{N}_{ij}^t + (1-\alpha)\mathbb{T}_j^{(t-1)} \quad (6)$$

where α represents the smoothing factor ($0 < \alpha < 1$). Therefore, $\mathcal{N}_j^{avg,t+1} = F_j^{t+1} = \mathbb{T}_j^t$. Similarly, we compute $\mathcal{N}^{avg}$ for each neighboring edge node of the i^{th} sensor node.

Reputation rating ($\mathcal{R}_j$): The reputation [11] of the j^{th} edge node is computed based on the positive (p_j^d) and negative (n_j^d) feedback about the j^{th} edge node. This positive or negative feedback is provided by the decision layer of the Safe-aaS infrastructure [1]. Depending on the time taken by the j^{th} edge node to process the sensor data during the past t time instants, feedback ($\mathcal{F}_j$) provided by the decision layer is:

$$\mathcal{F}_j^t = \begin{cases} p_j^{d,t}, & \text{if } t < t^{thr} \\ n_j^{d,t}, & \text{if } t > t^{thr} \end{cases} \tag{7}$$

where t^{thr} represents the maximum allowable time for computation such that $1 > p_j^{d,t} \geq x$, $x > n_j^{d,t} \geq 0$, and $p_j^{d,t} + n_j^{d,t} = 1$. x denotes the boundary value below which the feedback is considered as negative, while above the value of x, the feedback is considered as positive. Therefore, $\mathcal{R}_j$ of the j^{th} edge node at the t^{th} time instant is represented as:

$$\mathcal{R}_j^t = \frac{p_j^{d,t} - n_j^{d,t}}{p_j^{d,t} + n_j^{d,t} + 2} \tag{8}$$

Thus, $\mathcal{R}_j$ over a time period, τ, is computed as $\frac{1}{\tau}\sum_{t=1}^{\tau}\mathcal{R}_j^t$. Further, $\mathcal{R}_j$ of all the neighboring edge nodes for the i^{th} sensor node is computed.

A. Game formulation

We use a cooperative coalitional [12] game-theoretic approach to solve the proposed problem, DENSE. In this game, the edge node, E, within the proximity of a sensor node, act as player. Among these edge nodes, the neighboring edge nodes of a sensor node form a coalition ($\mathbb{C}$) such that each $\mathbb{C} \subseteq \mathcal{E}$. Each of the player in the game receives an utility called the *payoff* (v). The coalition game is a *transferable utility* (TU) game, which is represented as a pair $(\mathcal{E}, v)$, where $\mathcal{E}$ represent the set of players, and v is the payoff received by each of the players. In a coalition, $\mathbb{C} \subseteq \mathcal{E}$, the edge nodes are always interconnected with each other in the form of a graph. We consider $\mathbb{B} = \{B_1, B_2, \cdots, B_w\}$ as the set of w possible disjoint coalitions defined as a partition of the set of edge nodes, $\mathcal{E}$, such that $\forall i \neq j$, $B_i \cap B_j = \phi$, and $\cup_{i=1}^{w} B_i = \mathcal{E}$. The game is mathematically defined as:

$$\eta = \{(E_j)_{(E_j \in \mathcal{E})}, \mathbb{N}_i, (\mathbb{U}_{B_i})_{i \in w}\} \tag{9}$$

where E_j represents the j^{th} edge node, which acts as a player. $\mathbb{N}_i$ denotes the neighborhood of the i^{th} sensor node and comprises of the neighboring edge nodes of the i^{th} sensor node. $\mathbb{U}_{B_i}$ represents the utility of the edge nodes, which are joined to form the coalition.

***Axiom* 1.** *The proposed TU coalition game $(\mathcal{E}, v)$ is superadditive, if and only if,*

$$v(\mathbb{C}_i \cup \mathbb{C}_j) \geq v(\mathbb{C}_i) + v(\mathbb{C}_j), \quad \forall \mathbb{C}_i, \mathbb{C}_j \subset \mathcal{E}, \text{ s.t., } \mathbb{C}_i \cap \mathbb{C}_j = \phi \tag{10}$$

Justification: In a TU game [12], superadditivity indicates that in any two disjoint coalitions, $\mathbb{C}_i$ and $\mathbb{C}_j$, the payoff received by the players, in case of coalition $\mathbb{C}_i \cup \mathbb{C}_j$ is same. If the players form a large coalition with disjoint coalitions, the value obtained is not less than the sum of the value of disjoint coalitions. Mathematically:

$$v(\mathbb{C}_i + \mathbb{C}_j) \geq v(\mathbb{C}_i) + v(\mathbb{C}_j) \tag{11}$$

where $\forall(\mathbb{C}_i, \mathbb{C}_j) \subset \mathcal{E}$ and $\mathbb{C}_i \cap \mathbb{C}_j = \phi$. Since the game is superadditive, the coalition formed by the edge nodes result in the formation of the grand coalition.

Any coalition, $\mathbb{C}_i$, is formed using D_{ij}^N, $\mathcal{AS}_j$, $\mathcal{N}_j^{avg}$, and $\mathcal{R}_j$ of the j^{th} edge node at the t^{th} time instant. The utility of $\mathbb{C}_i$ is mathematically represented as: $\mathbb{U}(D_{ij}, \mathcal{AS}_j, \mathcal{N}_j^{avg}, \mathcal{R}_j)_{B_i}$. With the increase in distance between a sensor node and edge node, the utility reduces. On the contrary, with the increase in reputation, available storage space, and average number of tasks executed per unit time, the utility of the edge node increases. Therefore, the utility function is mathematically represented as:

$$\mathbb{U}_{B_i} = e^{\lambda_1 \mathcal{R}_j}\left(\frac{\lambda_2}{D_{ij}^N}\left(\lambda_3 \mathcal{AS}_j^x + \lambda_4 \mathcal{N}_j^{avg}\right)\right) \tag{12}$$

where λ_1, λ_2, λ_3, and λ_4 are the weight factors such that $\forall \lambda_i$, $0 < \lambda_i \leq 1$. x denotes the power of $\mathcal{AS}_j$, which shows the importance of the available storage space.

Lemma 1. *The influential values of the controlled factors such as available storage space ($\mathcal{AS}_j$) is set in such a way that the effects of the uncontrolled factors such as distance (D_{ij}^N), reputation rating ($\mathcal{R}_j$), and average number of tasks executed per unit time ($\mathcal{N}_j^{avg}$) are optimized.*

Proof: The outcome or response of a process may be modeled as the function of *controllable* and *uncontrollable* factors [13]. The factors, which can be altered during the experiment, are said to be controllable. On the other hand, the factors, which cannot be modified during the experiment, are known as uncontrollable factors. We assume the utility ($\mathbb{U}_{B_i}$) as an outcome or, response of the experiment. Therefore, $\mathcal{AS}_j$ can be modeled as controllable factor. The other factors such as D_{ij}^N, $\mathbb{R}_j$, and $\mathcal{N}_j^{avg}$ can be modeled as uncontrollable factors. Mathematically:

$$\mathbb{U}_{B_i} = \mathbb{U}(C_f, C_{uf})_{B_i} \tag{13}$$

where C_f and C_{uf} represent the controllable and uncontrollable factors respectively. The first-order derivative of Equation (13) gives:

$$\triangledown \mathbb{U}_{B_i} = \frac{\partial \mathbb{U}_{B_i}}{\partial C_f}\triangledown C_f + \frac{\partial \mathbb{U}_{B_i}}{\partial C_{uf}}\triangledown C_{uf} \tag{14}$$

Further, equating Equation (14) to zero we get:

$$\frac{\partial \mathbb{U}_{B_i}}{\partial C_f}\triangledown C_f = -\frac{\partial \mathbb{U}_{B_i}}{\partial C_{uf}}\triangledown C_{uf} \tag{15}$$

Thus, it is proven that the effects of uncontrolled factors can be optimized by setting the values of the controlled factors. ■

B. Existence of Equilibrium

We optimally select the appropriate edge node considering the amount of available storage space. Thus, in order to find the optimal value of storage space, at which the utility attains maximum, we compute the equilibrium condition. The existence of equilibrium is depicted in the Theorem 1.

Theorem 1. *The equilibrium condition of the set of neighboring edge nodes ($\mathcal{E}$) of the sensor nodes to form a coalition is mathematically represented in Equation (16).*

$$\mathbb{U}(D_{ij}^N, \mathcal{AS}_j^x, \mathcal{N}_j^{avg}, \mathcal{R}_j)_{B_i} \leq \mathbb{U}(D_{ij}, \mathcal{AS}_j^{x,*}, \mathcal{N}_j^{avg}, \mathcal{R}_j)_{B_i} \tag{16}$$

Proof: In order to attain the optimal solution, we maximize Equation (12), subject to certain constraints, as given in the Equation (18).

$$\underset{\mathcal{AS}_j}{argmax} \quad e^{\lambda_1 \mathcal{R}_j}\left(\frac{\lambda_2}{D_{ij}^N}\left(\lambda_3 \mathcal{AS}_j^x + \lambda_4 \mathcal{N}_j^{avg}\right)\right) \tag{17}$$

subject to,

$$\mathcal{R}_j \geq 0, D_{ij} \leq r_i^c, \mathcal{AS}_j^r \leq \mathcal{AS}_j^{init}, \text{ and } \mathcal{N}_j^{avg,t} \leq \mathcal{N}_j^{max} \tag{18}$$

$$\mathbb{L} = -e^{\lambda_1 \mathcal{R}}\left(\frac{\lambda_2}{D_{ij}^N}\left(\lambda_3 \mathcal{AS}_j^x + \lambda_4 \mathcal{N}^{avg}\right)\right) - \mu_1 \mathcal{R} + \mu_2\left(D_{ij}^N - r_i^c\right) + \mu_3\left(\mathcal{N}_j^{avg,t} - \mathcal{N}_j^{max}\right) + \mu_4\left(\mathcal{AS}_j - \mathcal{AS}_j^{init}\right) \tag{19}$$

where r_i^c represents the communication range of the i^{th} sensor node. The maximum number of tasks executed per unit time of the j^{th} edge node is denoted as $\mathcal{N}_j^{max}$.

The *Lagrangian* function of the Equations (17) and (18) are mathematically represented in Equation (19), where μ_1, μ_2, μ_3, and μ_4 are the *Lagrangian* multipliers. We apply *Karush-Kuhn-Tucker* (KKT) conditions to compute the optimal solution. The *dual feasibility* and *complementary slackness* conditions for each of the factors is represented in Equations (20) and (21).

$$\nabla_{\mathcal{AS}_j}\mathbb{L} = -e^{\lambda_1 \mathcal{R}_j}\left(x\frac{\lambda_2}{D_{ij}^N}\lambda_3\right)\mathcal{AS}_j^{(x-1)} + \mu_4 = 0 \quad (20)$$

$$\mu_i(\mathbb{X}) = 0, \text{ and } \mu_i \geq 0, \quad \forall i = \{1,2,3,4\} \quad (21)$$

where $\mathbb{X}$ represents the constraints of the Equation (18). The *Lagrangian* multiplier is denoted by μ_i.

The optimal value of the normalized available storage space to select the j^{th} edge node is represented as:

$$\mathcal{AS}_j^{opt} = \left(\frac{\mu_4 D_{ij}^N}{x\lambda_2\lambda_3 e^{\lambda_1 \mathcal{R}_j}}\right)^{\frac{1}{(x-1)}} \quad (22)$$

Therefore, we find the set of edge nodes among all the neighboring nodes to form a coalition. After the set of edge nodes is found, we compute the individual utility for each of the edge nodes. The edge node with the maximum utility is selected for processing the raw sensor data. ■

Algorithm 1 DENSE

INPUTS: $\mathcal{E}$, $\mathcal{F}_j^t$, $\mathbb{N}_i$, r_i^c, and $\mathcal{N}_j^{max}$.
OUTPUT: Optimally selected edge node for processing sensor data.
PROCEDURE:

```
for j = 1 to p do                                  ▷ p: Total no. of edge nodes
    while E_j is in N_i do
        Compute D_ij, R_j, AS_j, and N_j^avg.
        if Equation 17 and 18 satisfied then
            Compute utility (U_{B_i}).
        else if
            then  Select the nearest edge node in N_i.
        end if
    end while
    if U_{C_i}^{bf} < U_{C_i}^{af} then    ▷ U_{C_i}^{bf}, U_{C_i}^{af}: Utility before and after coalition
        E_j merges into C_i
    else if
        then  E_j splits from the coalition.
    end if
end for
Compute the individual U of edge nodes in B_i, E_j with maximum utility is selected.
```

V. Performance Evaluation

In this section, we analyze the performance of the proposed scheme, DENSE. The simulation parameters are given in the Table I. We execute our experiment upto 100 iterations with 95% confidence interval in the presence of 100-700 sensor nodes and 50-350 edge nodes.

Number of edge nodes: Fig. 2 illustrates the variation in the number of edge nodes in a cluster for different type of sensor nodes such as sensor type A, B, and C. Along the x-axis, we vary the number of iterations upto 30. We observe that the number of edge nodes in a cluster varies randomly with the iterations. Further, we also observe that with the increase in the total number of edge nodes in the simulation area, the number of edge nodes in a cluster increases. One of the possible reasons behind this is that with the mobility of the vehicles, the sensor nodes placed in them also become mobile. Therefore, the number of edge nodes present within their proximity also changes accordingly.

TABLE I: Simulation Parameters

Parameter	Value
Simulation area	$10\ km \times 10\ km$
Number of types of sensor nodes	5
Number of types of edge nodes	3
Number of sensor nodes	100-700
Number of edge nodes	50-350
Deployment type	random

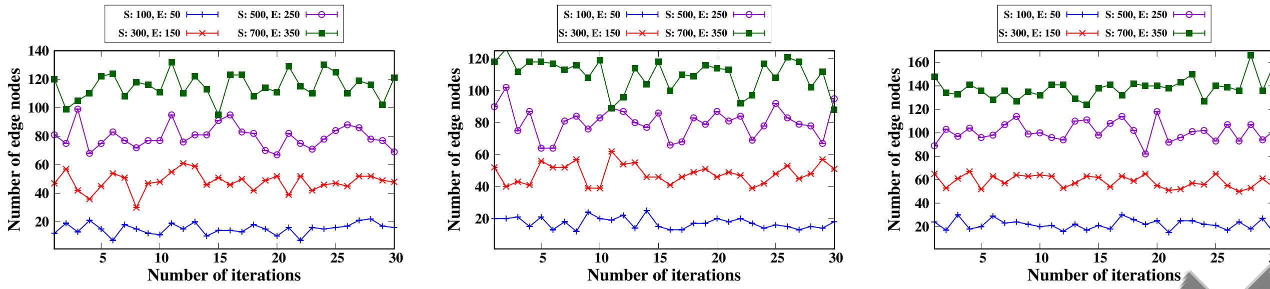
Distance between sensor node and neighboring edge node: Fig. 3 depicts the variations in the distance between the sensor node and the edge nodes within their proximity in a cluster for sensor type A, B, and C. We vary the time along the x-axis in the steps of 10. Interestingly, we observe that the distance between the sensor nodes and their neighboring edge nodes vary randomly with respect to time. The probable reason is that with the mobility of vehicles, the location of mobile sensor nodes change. Consequently, the number and type of edge nodes present within the proximity of that sensor node also varies. Therefore, the minimum distance between the mobile sensor node and its neighboring edge nodes changes with time. However, the distance between the static sensor nodes and their neighboring edge nodes remains constant. The average variation in the distance of the sensor type A, B and C change.

Average utility: Fig. 4 illustrates the variation in the utility of the edge nodes with the available storage space, distance, and average number of tasks executed per unit time. In fig. 4(b), we vary the distance from 0.1 upto 1, in steps of 0.1, along the x-axis. Similarly, for Figs. 4(a) and 4(c), along x-axis, we vary the available storage space and the average number of tasks executed per unit time in steps of 0.1. In Fig. 4(a), we observe that with the increase in the available storage space, the utility of edge node increases. In Fig. 4(b), we observe that with the increase in distance between the edge node and sensor node, the utility follows a decreasing trend. In Fig. 4(c), we observe that there exists an increasing trend in the utility of edge node with respect to the average number of tasks executed.

VI. Conclusion

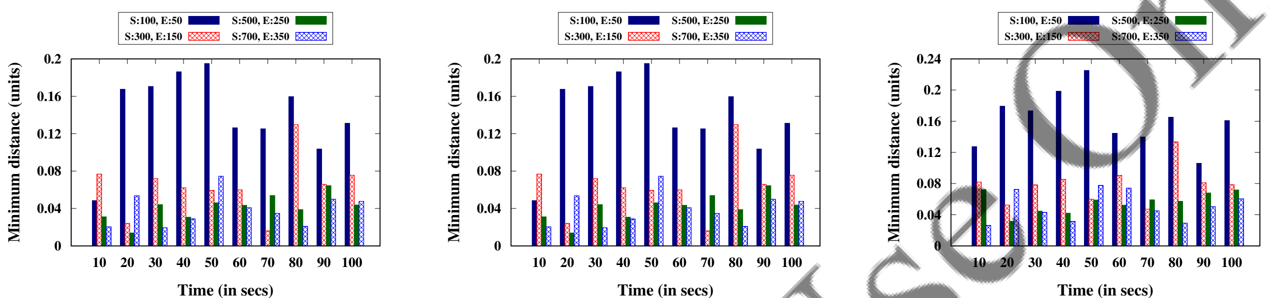
This work presented an edge node selection scheme for the Safe-aaS architecture. In a Safe-aaS infrastructure the presence of both static and mobile sensor nodes are considered. With the variation in the geographical location of the vehicles, the number of neighboring edge nodes in the vicinity of the mobile sensor node vary. Further, the storage capacity and average number of task execution capability is different for each type of edge node. Therefore, dynamic selection of edge node is essential. In order to select the appropriate edge node, we used cooperative coalition based game-theoretic approach. We formulated a *Mixed Integer Linear Program* (MILP) and solved it using *Karush Kuhn Tucker* (KKT) conditions. The simulation results depicted that the number of neighboring edge nodes of any sensor node vary randomly, and correspondingly the distance between the sensor node and edge nodes also varies.

In the future, we plan to explore the dynamic load sharing mechanism, among the edge nodes. Additionally, we target to work on the pricing model, among the various actors of the Safe-aaS architecture.



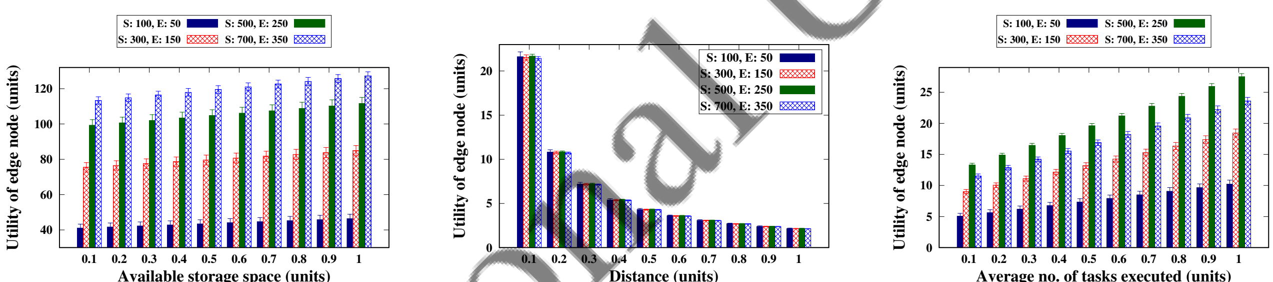
(a) Sensor type A (b) Sensor type B (c) Sensor type C

Fig. 2: Variation of the number of edge nodes in a cluster



(a) Sensor type A (b) Sensor type B (c) Sensor type C

Fig. 3: Variation of minimum distance between sensor node and its neighboring edge node



(a) Available storage space (b) Distance (c) Average number of tasks executed per unit time

Fig. 4: Variation of utility with various parameters

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