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EnTruVe: ENergy and TRUst-aware Virtual Machine allocation in VEhicle fog computing for catering applications in 5G

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ABSTRACT

It is undoubted that fog computing contributes in catering the latency-stringent applications of 5G, and one of the enabling technologies that fundamentally ensures the success of fog computing is virtualization as it offers isolation and platform independence. Although the emergence of vehicle-based fog (referred to as v-fog) facilities can certainly benefit from these desirable features of virtualization, there are several challenges that need to be addressed in order to realize the full potential that v-fogs can offer. One of the challenges of virtualization in v-fog is Virtual Machine (VM) migration. There are several factors that trigger a VM migration in a v-fog such as vehicle resource depletion. VM migrations would not only lead to nonessential usage of valuable resources (e.g. energy, bandwidth, memory) in the v-fogs, but also incur various overheads and performance degradation throughout the whole network. Thus, minimizing VM migrations is necessary. Furthermore, to ensure the seamless VM migrations between v-fogs, trust of v-fogs is required. While there exists studies of trust in the virtualization of cloud, they are irrelevant to v-fogs as v-fogs are different in nature (i.e. heterogeneous, mobile) from the cloud. Additionally, trust is not included in the decision making mechanisms of VM allocation for vehicular environments in the existing works. Moreover, as vehicle resources are constrained, their energy has to be utilized efficiently. In this paper, we propose EnTruVe, an ENergy and TRUst-aware VM allocation in VEhicle fog computing solution that aims to minimize the number of VM migrations while reducing VM processing associated energy consumption as much as possible. The VM allocation algorithm in EnTruVe provides a larger selection pool of v-fogs that meets the VMs requirements (e.g. trust, latency), thereby ensuring higher chances of success of VM allocation. Using Analytic Hierarchy Process (AHP), the proposed EnTruVe solution evaluates the v-fogs based on a set of metrics (e.g. energy consumption and end-to-end latency) to select the optimal v-fog for a VM allocation. Results obtained demonstrate that EnTruVe has the least number of VM migrations and it is the most energy efficient solution. Additionally, it shows that EnTruVe provides the highest utilization of v-fogs of up to 57.6% in comparison to other solutions as the number of incoming requests increases.

1. Introduction

As we enter the fourth industrial revolution, it is imperative for 5G networks to provide diverse services to cater to the stringent requirements of existing and upcoming applications. Fog computing [1] certainly plays an important role in realizing the potential of 5G with its capability in serving applications with stringent latency requirements and being close to end users. As vehicular technologies are advancing, combined with the fact that vehicles remain parked 96% of the time [2], parked vehicles can be utilized to serve as part of fog computing facilities. Thus, investment in deploying dedicated fog computing infrastructures for the end users can be reduced. In this paper, we define any device (e.g. routers, set-top box, and optical line terminal [3]) that has capabilities for catering edge computing services as fogs, and when the device is mobile, it is defined as v-fog.

Being the foundation in cloud computing, virtualization technology allows resources to be utilized efficiently where it creates an abstraction layer over computer hardware that allows

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the hardware elements of a single computer (processors, memory, and storage) to be divided into multiple Virtual Machines (VMs) [4]. The virtualization technology offers hardware-level isolation and platform independence [5], which is especially crucial to facilitate vehicular-based fog computing efficiently as seen employed in existing studies [6,7].

In contrast with cloud, v-fogs exert a distinctive set of challenges that should be overcome if virtualization is going to be employed. On top of having lower reliability, being distributed and mobile in nature, v-fogs are more vulnerable to attacks as the existing vehicular security measures cannot entirely prevent advanced attacks from happening [8,9]. This can not only jeopardize the v-fogs, but also endanger human lives. Thus, meeting the stringent latency and ensuring high availability are more challenging in fog-integrated 5G environment as these factors should be considered in making decisions related to VM management. Hence, a trust-based solution is required to facilitate VM-based fog computing platforms efficiently [5]. Similar to [10], we define trust as an expectation that a parked v-fog will behave in an intended manner. Trust is important as it enables seamless collaboration in the entire system, and without it, the deployment of v-fogs to assist 5G networks would be problematic.

Trust is not only imperative in fog computing and 5G, but it is also a persistent issue in the cloud [11]. Various studies of trust management are observed across multiple domains such as the Internet of Things (IoTs) [12,13], Wireless Sensor Network (WSN) [14], Intelligent Transport Systems (ITSs) [9] and cloud computing [15]. In cloud computing specifically, the authors in [15] presented a trust model specifically designed to assist cloud providers in taking decisions about inter-cloud VM migration based on reliability and reputation. Meanwhile, work in [16] uses a token-based approach to guarantee that VMs are migrated to trustworthy cloud platforms. However, no results are presented to support their frameworks. Additionally, trust is not emphasized in VM allocation in vehicles in the existing studies [17].

Due to the aforementioned limitations that fog computing faces i.e. being distributed, mobile, and vulnerable in nature, the existing trust-based VM allocation solutions in the cloud are not completely applicable to the vehicular environment. Nonetheless, trust in fog computing is highlighted in our previous work in [18] where we use a use case to demonstrate how our trust-based solution works. In our other work in [19], a trust-based task mapping solution between the v-fogs is proposed where parked v-fogs which are used as part of the fog computing facilities are clustered together for computation to form a physical cluster (known as Trust Domain) as shown in Fig. 1. Whereas logical cluster of v-fogs, as shown in Fig. 2 is based on the v-fog's trust value. Seeing the positive results, here we take a step further in extending our study considering the importance of trust inclusion in tackling the VM migration issue in v-fog. When trust is incorporated into VM management in v-fogs in terms of v-fog trust evaluation, we believe that reducing of the number of VM migrations and VM resource footprint, and increasing the v-fog energy efficiency can be achieved in which we will observe in the performance evaluation. We present a use case to highlight the importance of our work. In the use case scenario, we envision a commercial metropolitan area with plenty parking spaces similar to the work in [20]. Various tasks from end users of different sectors would be operating in the area such as health monitoring, real-time surveillance and tactile internet applications. Such critical tasks rely on stringent latency communication, hence the parked vehicles in the parking spaces can be utilized as fog computing facilities to locally process the tasks. This ensures that not only the stringent latency is met, but even security is considered.

To the best of our knowledge, this is the first study to incorporate trust in deciding the optimal vehicular fog node for VM allocation. Here, a VM allocation can refer to either VM placement or VM migration. We define VM placement as an event that occurs when a VM is placed to a host (v-fog) for the first time. When several conditions such as when the host is no longer meeting the VMs requirements or the host is moving elsewhere, VM migration is triggered. We define VM migration as an event that occurs when a VM is already placed onto a host but needs to be moved to another host due to factors such as not meeting the VMs requirements or the host is moving elsewhere. Note that VM migration is resource-intensive i.e. it consumes a large number of CPU cycles and network bandwidth [21] which in turn exhausts the v-fogs energy and can directly impact the v-fogs performance. Therefore, in this paper, we propose a solution named EnTruVe which has two major objectives: (i) reducing the number of VM migrations between the v-fogs and (ii) minimizing the energy consumption of v-fog based fog computing infrastructure when the virtualization technology is in place.

This paper is a follow-up work from our previous works presented in [18] and [19]. Motivated by the significance of trust inclusion in making VM allocation decisions that we discussed earlier, we aim to provide a trust-based service in order to meet a client's satisfaction such as finishing tasks on time. First, EnTruVe matches a client's request requirements with a VM. Then EnTruVe allocates the VM onto an optimal v-fog. EnTruVe consists of three VM allocation options namely (i) intra-cluster, (ii) inter-cluster, and (iii) inter-Trust Domain,[1] as shown in Fig. 3. These VM allocation options are further elaborated in Section 3.3.3 of this paper. Additionally, the proposed EnTruVe solution facilitates VM migration trigger algorithm that is executed when any of the trigger conditions is true. This is explained in Section 3.3.4 of this paper. Using Analytic Hierarchy Process (AHP), the proposed EnTruVe solution evaluates the v-fogs within the selected trust domain based on a set of metrics (e.g. energy consumption and end-to-end latency for a client that is requesting for a service) to select the optimal v-fog for a VM allocation.

Through this solution, we can reduce the number of VM migrations between the parked v-fogs, thereby increasing the utilization of the parked v-fogs and reducing valuable resources (e.g. energy, bandwidth, and memory) in the v-fogs. Additionally, EnTruVe selects the most energy-efficient parked v-fog and communication interface while assigning a VM to a v-fog in order to minimize the energy consumption in the v-fog based fog computing infrastructure. Hence, we make the following contributions in this paper:

- We consider trust as a variable to gauge the v-fogs performance and use it as the basis to form v-fog logical clusters. This is necessary considering v-fogs heterogeneous and distributed nature.
- We propose EnTruVe, a VM allocation solution that filters the participating v-fogs in Vehicular Fog Computing (VFC) in order to select the optimal v-fog for VM allocation using AHP.
- Our proposed VM allocation procedure takes into account the trust requirement of the VMs. This can be carried out in three options, namely intra-cluster, inter-cluster and inter-Trust Domain.
- Our solution selects the most energy-efficient parked v-fog while assigning a VM to a v-fog. Additionally, it considers the energy consumption of a v-fog's communication

[1] Intra-cluster VM allocation happens between v-fogs that reside in the same logical cluster and Trust Domain. Inter-cluster VM allocation occurs between v-fogs in the same Trust Domain but different logical clusters. Inter-Trust Domain VM allocation occurs between v-fogs from different Trust Domain but can be in the same or different logical clusters.

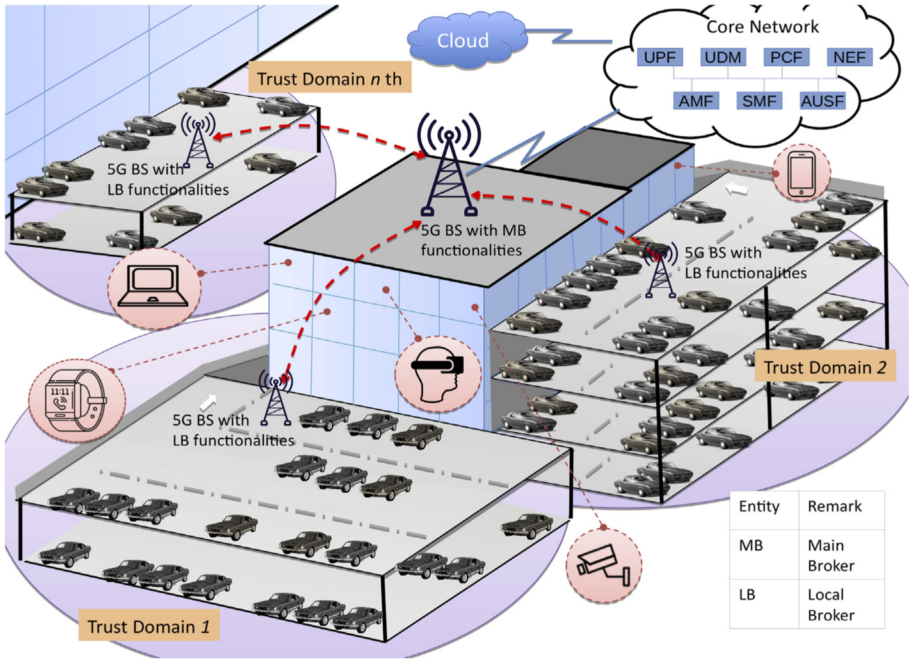


Fig. 1. v-fogs in different Trust Domains.

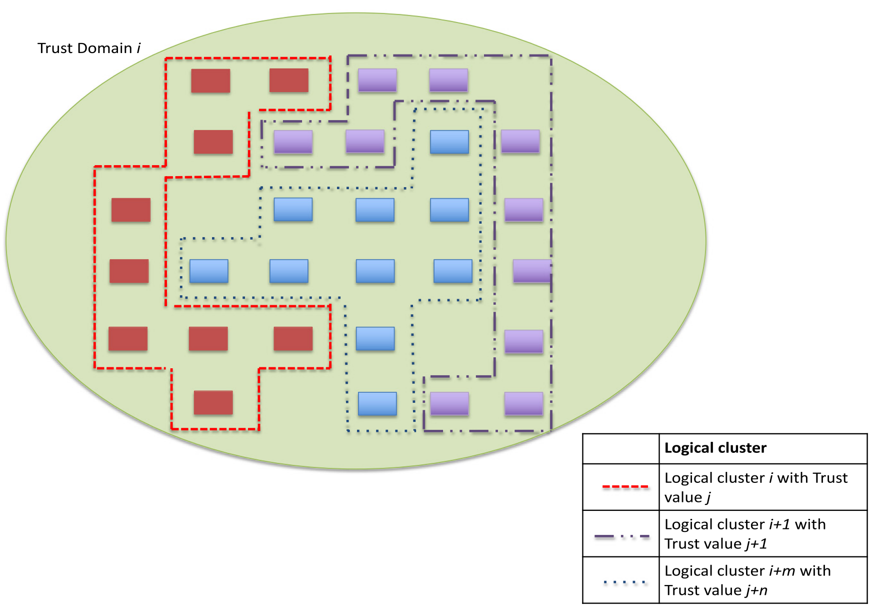


Fig. 2. Logical clusters in a Trust Domain.

interface of either Vehicle-to-Vehicle (V2V) or Vehicle-to-Interface (V2I), and dynamically selects the most energy-efficient communication interface for VM allocation onto the v-fogs.

The performance evaluation of the proposed work is conducted using Matlab. Our results demonstrate that the proposed EnTruVe solution outperforms the other solutions in terms of number of migrations, utilization, and energy efficiency. The rest of the paper is arranged as follows: Section 2 presents the existing studies on trust in VM management and VM allocation in the vehicular network. Section 3 describes the proposed work, system model and algorithm for VM allocation in v-fogs. The performance evaluations are elaborated in Section 4. Meanwhile the discussions and conclusions are presented in Sections 5 and 6, respectively.

2. Background study

In this section, we briefly review the existing studies pertaining to trust in the cloud in Section 2.1, and VM allocation in cloud and fog environments in Section 2.2.

2.1. Trust in cloud

There are studies on trust in the cloud that specifically focus on the Infrastructure-as-a-Service (IaaS) [15,22,23]. The authors in [22] propose CloudTrust that quantifies the degree of confidentiality and integrity offered by a Cloud Service Provider

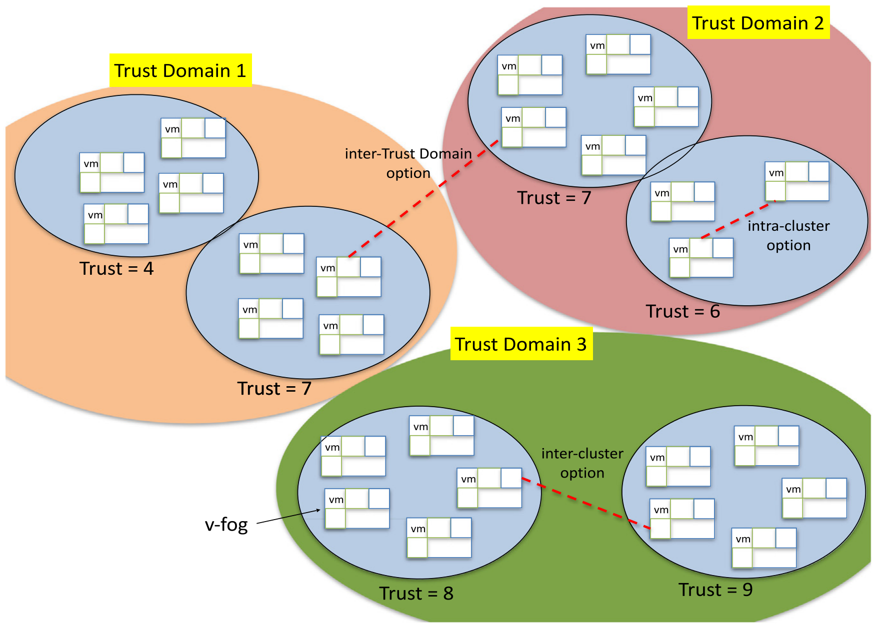


Fig. 3. VM allocation options in the proposed EnTruVe.

(CSP), where they also define physical and virtual trust zones. However, their trust assessment model is security-wise only and is not conducted to further secure VM migrations. Unlike [22], the authors in [23] propose a trusted VM migration protocol which can guarantee the coherence and continuity of trusted status during the VM migration in the IaaS platform. Their notion of trust is based on physical security such as digital signature. Meanwhile, the authors in [15] present a trust model specifically designed to assist cloud providers in making inter-cloud VM migration decisions. They assume that a truster computes the trust by means of two different measures: reliability, i.e. a direct measure derived by the direct experience of the truster with the trustee, and the reputation, which is an indirect measure based on the opinions of the other agents. However, no results are presented to support their framework. On the other hand, the authors in [24] develop a secure and intelligent task offloading framework where they exploit blockchain and smart contract to facilitate fair task offloading and mitigate various security attacks. The authors design a subjective logic-based trustfulness metric to quantify the possibility of task offloading success, and develop a trustfulness assessment mechanism. An online learning-based intelligent task offloading algorithm named QUeuing-delay aware, handOver-cost aware, and Trustfulness Aware Upper Confidence Bound (QUOTA-UCB) is proposed, which can learn the long-term optimal strategy and achieve a well-balanced tradeoff among task offloading delay, queuing delay, and handover cost.

Authors in [16] propose a secure and trustworthy solution for VM migration within an existing cloud provider domain. Using a token-based approach, their solution guarantees that VMs are migrated to trustworthy cloud platforms. On the other hand, the work in [25] presents a trust model to support service providers to verify trustworthiness of infrastructure providers in cloud computing environments. Their model calculates trust values based on different parameters, namely Service Level Agreement (SLA) monitoring compliance, service provider ratings, and service provider behavior. Finally, the trust values are calculated based on an opinion model in terms of belief, disbelief, uncertainty and base rate. However, their trust evaluation is not incorporated in the VM migration procedure.

2.2. VM allocation

To achieve the optimization of channel selection which is critical for efficient and reliable task delivery in edge computing environment, the authors in [26] propose a learning-based channel selection framework with service reliability awareness, energy awareness, backlog awareness, and conflict awareness, by leveraging the combined power of machine learning, Lyapunov optimization, and matching theory. Resource allocation in terms of VM allocation has been vastly studied over the years with different objectives such as preventing SLA violations, reducing the number of transferred pages, reducing the number of physical machines, and the number of migrations [27]. Several studies have attempted to address the VM allocation issue in cloud data centers. It is addressed in [28] where the authors use an Ant-Colony system-based approach in order to minimize the number of active servers, improve the resource utilization, balance different resources, and reduce power consumption. Another study in [29] focuses on minimizing data and energy cost of VM allocation in distributed cloud data centers. The authors in [30] introduce VMPlanner which optimizes the traffic flow routing to turn off as many unneeded network elements as possible for power saving. Meanwhile, the study in [31] presents a solution by placing the VMs according to each host capacity. The authors propose an enhanced levy-based particle swarm optimization algorithm with variable-sized bin packing to solve the VM placement problem. VM migration is triggered when the utilization rate of VM reaches a critical value.

In v-fog, the authors in [17] present a mobility and destination workload-aware migration scheme which takes into account the workload and mobility of the original host as well as the potential destinations. This ensures that the destinations have time to process the current workload and migrate new workload when required. To avoid the second-hop problem, they utilize cutoff calculation to calculate the cutoff time for the search criteria where only vehicles remaining in the grid longer than cutoff are considered as viable candidates. The source vehicle consequently selects the vehicle with the longest time remaining among the viable candidates for workload migration. A close resemblance to our proposed idea can be observed in [32] where the authors envision four types of VM migrations in v-fog, namely inter-fog, intra-fog, across roadside-vehicular cloud, and across roadside-central cloud. However, the basis of host selection for allocation of VMs is not justified and trust is not integrated in their VM migration types.

Similar studies addressing the above issue can be seen in [33]. The authors in [33] aim to achieve minimal average data traffic where they propose an enumeration based optimal placement algorithm and divide-and-conquer based near-optimal placement algorithm. They distribute the VM Replica Copies (VRCs) of applications to the edge network, enumerate all placements of VRCs and evaluate the average data traffic for each placement case. However, End-to-End (E2E) latency is not considered in the studies mentioned above. As E2E latency is an essential factor that needs to be considered for VM allocation in fog environment, it is considered in some studies (e.g. [34–36]). In [34], the authors propose a VM allocation decision model based on mobility prediction in fog computing in order to optimize the placement of the VMs in a v-fog. In their study, the VM is moved to a v-fog node ahead of its route which aims to reduce user latency. They use a greedy algorithm to select the fog with the lowest E2E latency among a set of 10 candidate fogs.

The authors in [36] use a modified Q-learning method on deciding the resource price strategy for VM migration. They develop a novel one-on-one contract game with 3 phases: VM migration decision, the conclusion of a contract for the v-fog resource allocation, and learning-based price adjustment. The closest study that resembles our work is found in [35] where the authors propose a VM migration decision policy named VaMPIre, that considers the mobility of vehicles and the number of resources available in the fogs. The authors use the AHP for decision-making, and consider four factors that can affect the VM migration decision namely the energy cost of performance, communication, mobility, and available resources.

It is apparent from the existing literature that although trust (mainly in terms of communication trust and data trust) is an important aspect specifically the cloud, it is not considered in VM allocation in the vehicular environment. We believe that providing a trust-based solution for VM allocation is important in ensuring a seamless virtualization-based collaboration in the VFC environment. Hence, we are motivated to provide a solution that infuses trust in the VM allocation procedure.

3. Proposed work

To facilitate this, we propose a framework that observes the VM allocation in v-fogs. Section 3.1 elaborates the system model, Section 3.2 describes our EnTruVe solution's workflow, and the proposed algorithm is presented in Section 3.3.

3.1. System model

In this study, we consider live VM migration in order to reduce the service downtime [27]. In our proposed solution, we consider that each client request has three main requirements i.e. trust, E2E latency requirement, and task completion time. We denote $V = \{vm_1, vm_2, \ldots, vm_n\}$ as the set of VMs in a v-fog where n is the number of VMs and $\sum_{i=1}^{n} vm_i \leqslant V_{cap}$, where V_{cap} is the capacity of VMs that a v-fog can hold. The set of requests from the clients is denoted as $R = \{r_1, r_2, \ldots, r_m\}$, where m is the number of requests. We assume that a VM allocation can take place with the help of brokers through either the V2V or V2I communications. The former enables the v-fog to communicate directly with the brokers via 5G or WiFi technologies. Meanwhile, the latter utilizes the Device-to-Device (D2D) connectivity using either the 5G D2D or WiFi Direct technologies [37] with network-assisted configurations. We assume that the brokers will prompt the Base Station (BS) to assist D2D-related processes such as D2D discovery and D2D synchronization [38] beforehand minimizing time consumption in D2D communication. We assume that the D2D facilitates the multiple-hop communication.

We assume a few additional network functions in a 5G core network similar to our work in [19]. We consider two additional components which are two levels of broker function located in the 5G BS, namely the Main Broker (MB) and Local Broker (LB), similar to our previous paper [19]. There are five main components involved in facilitating the VM allocation in our proposed EnTruVe, namely User Plane Function (UPF), MB, LB and the v-fogs as explained below:

1. **UPF**: Apart from having its existing functions in 5G networks such as packet inspection, traffic steering of the user plane, and transport-level packet marking [39], we assume that the UPF has a global knowledge including the traffic forwarding latency from one point to another point similar to our previous work in [19]. Additionally, we assume that the UPF has the Workload Management (WLM) subcomponent as shown in Fig. 4, which keeps a record of VMs that will be placed and are currently being placed in a v-fog, and the workload status of a v-fog. The WLM also contains information of a v-fog namely E2E latency, energy consumption, and resource availability, which are further explained in the subsequent subsection.
2. **LB**: The LB runs the v-fog admission procedure which performs the trust evaluation of v-fogs using the metrics and the procedure explained in our previous study. As trust values are dynamically changing over time, the LB periodically evaluates the trust values of the v-fogs.
3. **MB**: The MB has a Request Management subcomponent which manages incoming requests generated by the clients. The role of MB is to allocate VMs to the most appropriate v-fog where it runs the VM allocation procedure that will be elaborated in Section 3.3.2. To execute the procedure, the MB requires the information from the 5G core network. A subcomponent in the MB called Analytic Hierarchy Process Evaluation (AHPE) executes the necessary steps (see the algorithm presented in Fig. 5) to evaluate and determine the optimal v-fog that meets the requirements of VM for task processing based on predefined metrics.
4. **VM Repository (VMR)**: To ensure centralized management of VMs, we assume that the VMR operates in the cloud similar to [40]. The VMR receives any incoming client requests from the MB. The functions of the VMR includes creating the VMs to cater to the application requirements of the request based on VM template, storing and destroying the VMs when required.
5. **v-fog**: Additionally, we consider that a v-fog in a logical cluster can execute various VMs created by the VMR. We assume that single or multiple VM allocations can occur from a v-fog. At a given time, there can be m VMs in a v-fog, therefore the total number of VM arrivals in a v-fog is expressed as $\lambda_{total} = \lambda_1 + \lambda_2 + \cdots + \lambda_n$, where n is the nth VM arrival. We assume that a v-fog can set its maximum utilization, ρ_{max} considering the service latency L_s set by the operator (this will be elaborated further in Section 3.3.1).

3.2. Proposed workflow

When a v-fog reaches a Trust Domain, the v-fog's information is first extracted from the 5G core network (1), as illustrated in Fig. 4. The LB acquires these information for the v-fog's trust evaluation in the v-fog admission procedure. On the other hand, the MB needs the v-fog information for decision-making in the VM allocation procedure. First, we explain here how the LB assigns a v-fog to a logical cluster. Next, we explain how the MB conducts the VM allocation procedure.

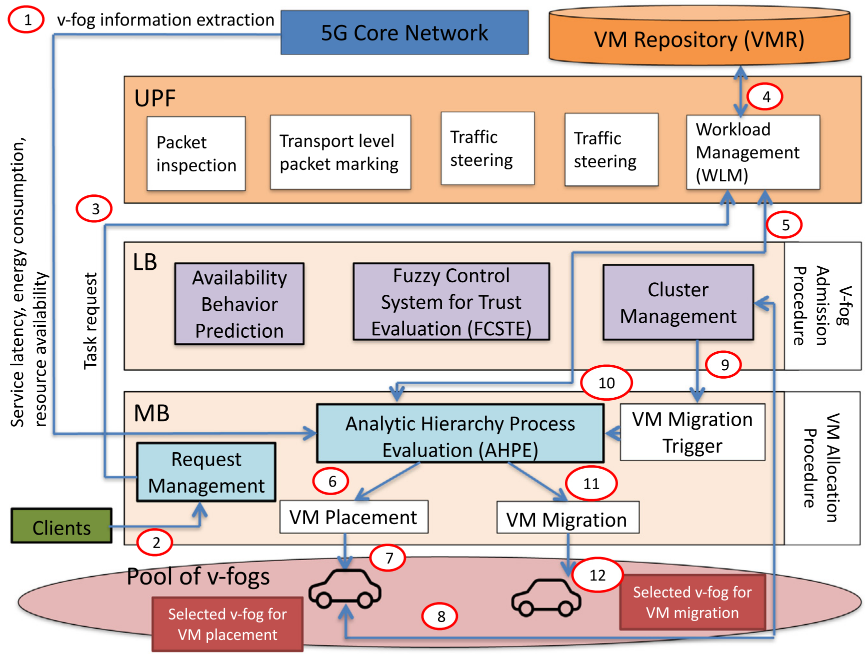


Fig. 4. General workflow of EnTruVe.

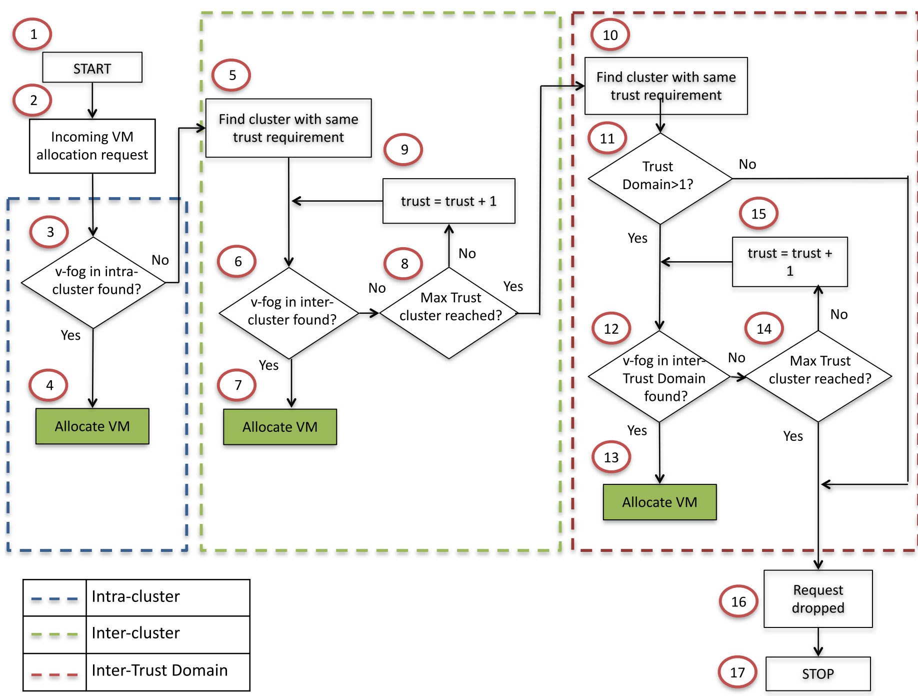


Fig. 5. Flowchart for VM allocation algorithm in MB.

3.2.1. v-fog admission procedure in a logical cluster

The LB evaluates the trust of a v-fog based on three metrics namely, availability, security and reputation. The security metric reflects the v-fog security level, reputation metric is measured based on a v-fog's performance in completing user requests, and the availability metric is measured in terms of the v-fog's parking duration. The logical clusters, which we defined in Section 1, are formed based on trust values. Each logical cluster has its own trust range, predefined by a lower bound and an upper bound, depending on the number of logical clusters. After the LB evaluates the trust value of a v-fog and if the v-fog's trust value falls into a logical cluster's trust range, the LB assigns the v-fog to the respective logical cluster. For instance, as illustrated in Fig. 2, a v-fog that belongs to logical cluster i can be promoted and assigned to logical cluster $i + 1$ when the v-fog's trust value is within logical cluster $i + 1$'s trust range. Similarly, the LB can demote the v-fog to other logical clusters if the v-fog's trust value falls within the other logical cluster's trust range. This demonstrates that trust is dynamic and the solution can cater to the changing trust values of v-fogs.

In this paper, the trust assessment of v-fogs is conducted using fuzzy logic in LB. The v-fogs' admission into their respective logical clusters according to their trust value is based on the Vehicle Cluster Formation algorithm in our previous work presented in [19]. The execution of this procedure is compulsory before the VM allocation procedure takes place.

3.2.2. VM allocation procedure

1. **VM Placement**:
For the VM allocation procedure in MB, Fig. 4 shows that a client sends a task request to the MB consisting of its requirements (2). To serve the task request, our proposed solution takes these requirements into account for allocating a VM to a v-fog. We define a vector $C = \{trust, E2E\ latency\ requirement, task\ completion\ time\}$, element of which respectively defines the client's trust, end-to-end latency and task completion deadline requirement for a particular task. The total time that a v-fog can serve is denoted by $V_{tp} = V_{park} + V_{leave}$, where V_{park} is the average v-fog parking duration and V_{leave} is the average time when the v-fog starts to leave its parking spot until it leaves the premise. If the v-fog's $V_{tp} < T_{proc}^{total}$, where T_{proc}^{total} is the total amount of time required to finish the tasks, the MB will not consider the v-fog for VM allocation. Upon receiving the task request, the Task Management component forwards the task request to the WLM in order to process it (3). Then the WLM acquires a VM from the VMR to cater the task request requirements (4). The WLM forwards the VM information to the AHPE (5), where the AHPE then selects a v-fog that meets the requirements (6) in order to reduce the number of VM migrations. Inevitably, there could be more than one v-fog that meet the requirements. Hence, the MB uses AHP in this procedure for VM allocation to select the optimal v-fog for VM allocation [41]. Based on the three options for VM allocation namely intra-cluster, inter-cluster, and inter-Trust Domain, the AHPE then identifies the optimal v-fog for VM placement (7). The v-fog periodically updates the LB of its current status while processing the VM at hand (8).
2. **VM Migration**: As mentioned previously, the LB periodically assesses the trust value of a v-fog. When the trust value of the v-fog at a given time t is depleted, the v-fog no longer meets the trust requirement of the VM and thus triggers the VM migration. At this point, we have an algorithm (that will be discussed in the following subsection) that handles VM migration that is triggered from different conditions. For instance, when the v-fog's security in terms of its authentication role has changed or its digital certificate to participate in the VFC service has expired, these can lead to the decrease in security value and subsequently depletes the v-fog's trust value. Similarly, if the v-fog's $V_{leave} < (T_{proc}^{total} - T_{cur}^{total})$, where T_{cur}^{total} is the current time elapsed in processing the tasks, this condition triggers the v-fog to migrate the VM to another v-fog. Another factor is when the E2E latency is no longer met for the client, which could happen due to the increase of network latency (L_n). When VM migration is triggered from a v-fog (9), the running VMs in the originating v-fog have to be migrated to other v-fog that meets the VM requirements. The AHPE evaluates the rest of the v-fogs that meets the VM requirements (10) and selects a v-fog to migrate the VM based on the same metric set (11). Similar to VM placement, the VM migration also follows the three mentioned VM allocation options (12). These options are described in Section 3.3.3.

3.3. Proposed algorithm for VM allocation

In this subsection, we evaluate the v-fogs in order to find the optimal v-fog for VM allocation. We define three metrics that are used for decision-making in our proposed algorithm. Then we explain the use of AHP to evaluate the metrics for optimized v-fog selection. Finally, we elaborate on our proposed VM allocation algorithm and the VM migration trigger algorithm. The notations which are used for mathematical expressions in this paper are tabulated in Table 1.

Table 1
Summary of key notations.

Notation	Definition
α_{tx}	Linear scaling factor for transmission
β_{tx}	Baseline power consumption of WiFi in active v-fog using WiFi (W)
λ	VM allocation request arrival rate to a v-fog
μ	v-fog's service rate
Ω_{max}^{v}	v-fog processor maximum processing capacity (MIPS)
EC_n	Total energy consumption of v-fog wireless interface (J)
EC_{dst}	Energy consumption of destination v-fog wireless interface (J)
EC_{int}	Energy consumption of intermediate v-fog wireless interface (J)
EC_{src}	Energy consumption of source v-fog wireless interface (J)
EC_{total}	Total energy consumption of a v-fog (J)
EC_p	Energy consumption of v-fog processor (J)
L	Observation period
L_{e2e}	E2E latency
L_n	Network latency
L_s	Service latency
M	Number of VMs to be migrated
$n(p)$	Number of each VM's iterations to migrate multiple VMs
P	Power consumption of v-fog communication interface
$P(b)$	Erlang B blocking probability
$P(l)$	Probability of link existence
P_{BB}	Baseband power consumption (W)
P_{idle}^{v}	v-fog processor idle power consumption (W)
P_{max}^{v}	v-fog processor maximum power consumption (W)
P_{on}	Power consumption when cellular subsystem is active (W)
P_{OH}	Additional power consumption of BS (W)
P_{RF}	Radio frequency block power consumption (W)
P_{V2V}	v-fog power consumption using V2V communication (W)
P_{V2I}	v-fog power consumption using V2I communication (W)
r	Ratio of dirtying rate of memory page to the VM transmission rate
R_{rx}	Data received rate (Mbps)
R_{tx}	Data transmission rate (Mbps)
R_{vm}	VM transmission rate (Mbps)
r_{max}	Maximum range between two v-fogs (m)
S_{tx}	Transmit power (W)
T_{tot}^{V2V}	Total latency using V2V communication
T_{tot}^{V2I}	Total latency using V2I communication
T_{SC}	Time taken for the source to send data to the LB
T_{SCD}	Time taken for the source to send data to the destination v-fog
T_{LB}	Time taken for the LB to send data to the next MB or v-fog
T_{MB}	Time taken for the MB to send data from the previous LB to the next LB
T_{down}	Migration downtime
T_{trans}	Transmission time
T_{prop}	Propagation time
T_{res}	The time a VM takes to resume its operation at destination v-fog
Vm	Original memory size of each VM (MB)
wl	Ratio of v-fog CPU capacity

3.3.1. Metrics for v-fog evaluation

We define three metrics namely E2E latency, energy consumption, and resource availability, that the MB uses for deciding on the optimal v-fog in the VM allocation procedure. Here, we explain the metrics:

1. **E2E Latency**: The L_{e2e} is considered as it has a significant impact on 5G applications. This is because the emerging applications such as haptics and robotics, augmented reality and virtual reality have time-sensitive requirements. Hence, selecting a v-fog that can meet the stringent E2E

latency requirement for VM allocation is crucial. L_{e2e} is comprised of service latency (L_s) and network latency (L_n) as expressed below:

$$L_{e2e} = L_s + L_n \tag{1}$$

It is worth noting that while L_s can be managed by the broker, calculating the L_n precisely is beyond the control of the VFC. These two latencies are described below:

- **Service Latency**: The L_s of a v-fog is set by the service provider. Therefore we can calculate L_s using (2) which is based on the average service delay of a v-fog calculation of the M/M/1 queuing model in [42] where μ_i is the service rate of ith v-fog and ρ_i is the utilization of ith v-fog.

$$L_s = \frac{\frac{1}{\mu_i}}{1-\rho_i}, \tag{2}$$

where μ_i is the service rate of ith v-fog and ρ_i is the utilization of ith v-fog. In order to get the desired L_s using (2), we set the maximum utilization of ith v-fog (ρ_{max}) as expressed in (3), and for a given set of v-fog, ρ_{max} is set by the service provider. In order to get the desired L_s using (2), we set the maximum utilization of ith v-fog (ρ_{max}) as expressed in (3), and for a given set of v-fog, ρ_{max} is set by the service provider.

$$\rho_{max} = 1 - \frac{1}{\mu_i L_s} \tag{3}$$

where $0 \leqslant$ *current utilization* $\leqslant \rho_{max}$. Furthermore, from (3), we can obtain the maximum arrival rate that a v-fog can accept, denoted as λ_{max} using (4).

$$\lambda_{max} = \rho_{max}\mu_i \tag{4}$$

- **Network Latency**: The L_n calculation differs for each communication type. When VM allocation occurs using V2V communication, L_n can be obtained from (5):

$$L_{n,v2v} = T_{SCD} * n \tag{5}$$

where T_{SCD} is the time taken for the source to send the data to the next receiving v-fog, and n is the number of hops between the v-fogs. If intra-cluster and inter-cluster VM allocations are conducted using V2I, the L_n can be expressed as $L_n = T_{SC} + T_{LB}$, where T_{SC} is the time taken for the source to send the data to the LB, and T_{LB} is the time taken for the LB to transfer data to the destination v-fog. Otherwise, the latency for inter-Trust Domain VM allocation is expressed as $L_n = T_{SC} + 2T_{LB} + T_{MB}$, where T_{MB} is the time taken for MB to transfer data from the source LB to the next LB as denoted in (6).

$$L_{n,v2i} = \begin{cases} T_{SC} + T_{LB}, & \text{if intra/inter-cluster} \\ T_{SC} + T_{LB} + T_{MB} + T_{LB}, & \text{otherwise.} \end{cases} \tag{6}$$

The latency in each of the node (T_{node}) i.e. T_{SCD}, T_{SC}, T_{LB}, and T_{MB} described above is comprised of transmission time (T_{trans}), propagation time (T_{prop}), and migration downtime (T_{down}) of the VM which are calculated as (7):

$$T_{node} = T_{trans} + T_{prop} + T_{down}. \tag{7}$$

Evaluating T_{down} is an important parameter that affects the latency as we deal with VMs with various memory size, number of VMs, and memory dirtying rate. We follow the work in [43] to evaluate the downtime of VM migration in (8) as follows:

$$T_{down} = \frac{MV_m}{R_{vm}} Mr^{n(p)} + T_{res}, \tag{8}$$

where M is the number of VMs to be migrated, R_{vm} is the VM transmission rate and r is the ratio of the dirtying rate of memory page to the transmission rate. The amount of original memory of each VM is Vm and $n(p)$ is the actual number of each VM's iterations in strategy for migrating multiple VMs and T_{res} is the time a VM takes to resume at the destination v-fog.

2. **Energy Consumption**: To measure the energy consumption of a v-fog in a given amount of time, we define L as the observation period. The calculation for energy consumption of a v-fog during L is expressed as $EC_{total} = EC_p + EC_n$, where EC_p is the energy consumption of the v-fog for processing a VM, and EC_n describes the energy consumption of the v-fog wireless interface during the observation period, L. Following [44], EC_p can be calculated as (9):

$$EC_p = \left(\frac{P^v_{max} - P^v_{idle}}{\Omega^v_{max}}\right) \cdot wl \cdot L, \tag{9}$$

where P^v_{max} is the v-fog processor maximum power consumption when $\lambda < \lambda_{max}$. Here, λ_{max} is obtained from (4). Meanwhile, P^v_{idle} is the v-fog processor idle power consumption, Ω^v_{max} is the v-fog processor maximum processing capacity (MIPS), and wl is the ratio of v-fog CPU capacity.
In both of the communication types i.e. V2V and V2I, we consider energy consumption in the source v-fog, all the intermediate nodes and the destination v-fog. We assume that the power is calculated from the source v-fog node to the intermediate nodes and destination v-fog node. For simplicity, we assume that the v-fogs have similar transmission and reception rates. Therefore, calculating the EC_n of a v-fog during L can be expressed as (10):

$$EC_n = E_{src} + nE_{int} + E_{dst}, \tag{10}$$

where E_{src} is the transmission energy consumption of the source v-fog to the intermediate nodes, E_{int} is the transmission and reception energy consumption of the intermediate nodes to the destination v-fog, and E_{dst} is the reception energy consumption of the destination node. The E_{src}, E_{int}, and E_{dst} are calculated using (11)–(13) respectively as follows:

$$EC_{src} = \frac{VM_{size}}{R_{tx}} \lambda LP, \tag{11}$$

$$EC_{int} = n(VM_{size} \cdot \lambda LP(\frac{1}{R_{tx}} + \frac{1}{R_{rx}})), \tag{12}$$

$$EC_{dst} = \frac{VM_{size}}{R_{rx}} \lambda LP, \tag{13}$$

where VM_{size} is the average VM memory size to be transferred, R_{tx} and R_{rx} are the transmitted and received data rate of the v-fog, respectively. The VM allocation request arrival is denoted as λ. Meanwhile P is the v-fog power consumption. As expressed in (14), $P = P_{V2V}$ if v-fog is using V2V communication, and $P = P_{V2I}$ if v-fog is using V2I communication, either via WiFi or 5G.

$$P = \begin{cases} P_{V2V}, & \text{if } \lambda < \lambda_{max} \\ P_{V2I}, & \text{otherwise ,} \end{cases} \tag{14}$$

We assume the equation provided in this paper for power consumption in 5G follows [45] and the calculations of P_{V2I} for WiFi follows the work in [37] as elaborated below:

$$P_{V2I} = \begin{cases} \alpha_{tx} R_{tx} + \beta_{tx}, & \text{if } WiFi, \\ P_{on} + P_{BB}(R_{tx}) + P_{RF}(S_{tx}) + P_{OH}, & \text{if } 5G, \end{cases} \tag{15}$$

where the parameter α_{tx} is a linear scaling factor for transmission and β_{tx} is the baseline power consumption in the active v-fog using WiFi connection. Whereas for communication using 5G, the P_{on} is the power consumption when the cellular subsystem is active, P_{BB} is the baseband power consumption which is dependent on R_{tx}, and P_{RF} defines radio frequency block power consumption that is dependent on the transmit power, S_{tx}. Meanwhile, P_{OH} is the additional power consumption of the BS which includes cooling and circuit loss.

3. **Resource Availability**: Availability is an important factor to consider for VM allocation, especially when dealing with mobile devices of limited resources and inconsistent power supply. The LB considers availability in trust evaluation of v-fog admission procedure based on the v-fog's parking duration. However, a v-fog can still be considered available although it is overutilized with requests. Thus, the chances of a v-fog being unavailable due to overutilization should be considered. Here, we observe resource availability in terms of the v-fog's blocking probability ($P(b)$) and the probability of link existence ($P(l)$). The resource availability can be calculated using (16),

$$UA = \alpha P(b) + \beta(1 - P(l)), \tag{16}$$

where α and β are the weightage score, and $\alpha + \beta \leqslant 1$. $P(b)$ can be obtained using the Erlang B blocking probability, depending on the λ (request arrival rate) and μ (v-fog's service rate). Following [46], we assume that the distance between two v-fogs which is needed in V2V communication follows the exponential distribution with path consisting of l links, and $P(l)$ is given by (17), where r_{max} is the maximum range between two v-fogs.

$$P(l) = \int_0^{r_{max}} \lambda e^{-\lambda s} ds = 1 - e^{-\lambda r_{max}}. \tag{17}$$

3.3.2. Decision making using AHP

The MB uses AHP [47] to make decisions in determining the optimal v-fog for VM allocation based on the defined metrics. Unlike fuzzy logic that is used for trust evaluation, the AHP method has criteria weights independent from the hierarchy's depth. AHP also has the ability to check for inconsistency in the decider's preferences [48]. Although the MB selects the optimal v-fog for VM allocation, there is a possibility that the selected v-fog may not meet the E2E latency requirement. Hence, prior to the decision-making using AHP, the MB filters the v-fogs that participate in the VFC where only v-fogs that meet the E2E latency requirement will be considered for the AHP evaluation. In the AHP evaluation, the number of criteria, n is defined for VM allocation based on set $M = \{energy\ consumption, E2E\ latency, resource\ availability\}$. A Pairwise Comparison Matrix (PCM) is generated for the criteria as expressed in (18):

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn}. \end{bmatrix}. \tag{18}$$

On the right and left sides of the matrix diagonal, the values represent the strength of agreement of ith criteria with respect to jth criteria [49]. Let $a_{ij} = 1/a_{ji}$ where $i, j = 1, 2, \dots, n$, $a_{i,j} > 0$ and $a_{i,j} = 1$. Saaty's scale [47] is used to determine the value of the (i, j) position of the PCM. The relative importance of various criteria is computed using the Normalization of the Geometric Mean (NGM) technique, and ω_i symbolizes the degree of importance for the ith criteria as expressed in (19).

$$\omega_i = \frac{(\prod_{j=1}^{n} a_{ij})^{\frac{1}{n}}}{\sum_{i=1}^{n}(\prod_{j=1}^{n} a_{ij})^{\frac{1}{n}}}. \tag{19}$$

Finally, the score for ith v-fog to each criteria (Vs_i) is calculated using (20):

$$Vs_i = min \sum_{n}^{j=1} \frac{a_{ij}}{\sum_{m}^{i=1} a_{ij}} \cdot \omega_i. \tag{20}$$

This paper assumes a minimization case where a v-fog with the lowest AHP score is selected as the optimal v-fog for VM allocation.

3.3.3. VM allocation algorithm in the MB

Here, we elaborate our proposed VM allocation algorithm that is illustrated in Fig. 5. Following the procedure in our previous work [19], a v-fog belongs in a Trust Domain upon entering a parking lot and is assigned to a logical cluster. The MB periodically obtains all the v-fog's information i.e. energy consumption, E2E latency and resource availability information in the background (1). When there is an incoming request of a VM that needs to be hosted in a v-fog (2), the MB has to select a v-fog with the lowest AHP score using (20). The MB uses the gathered information for v-fog evaluation and goes through the three VM allocation options in sequence starting from intra-cluster, then the inter-cluster, and lastly the inter-Trust Domain.

- Intra-cluster: The MB starts by observing the first option and evaluates the v-fogs belonging in the same logical cluster for VM allocation (3). The VM is allocated when there is an optimal v-fog (4), and prior to the allocation, the MB selects the communication path of either V2V or V2I, that offers the lowest E2E latency. If no suitable v-fog in the intra-cluster option that meets the VM requirement is found, the MB proceeds to consider the inter-cluster option where the same steps are applied (5).
- Inter-cluster: For the second option, the MB only consider logical clusters with trust range which is equal to or greater than the VM trust requirement[2] (in case of VM placement) or the logical cluster with the same trust range as the originating v-fog belongs to (in case of VM migration) (6). Similar to the intra-cluster option, the MB selects the communication path of either V2V or V2I, which offers the lowest E2E latency before allocating the VM when the optimal v-fog is found (7). When no optimal v-fog is found, the MB proceeds to search in logical clusters in an ascending manner (8) until there is no optimal v-fog found in the logical cluster with the highest trust value in the Trust Domain (9). This prompts the MB proceeds to search in the last option (10).
- Inter-Trust Domain: In the final option, the MB first observes the nearest Trust Domain (11) and begins searching the logical cluster with the same trust range as the VM trust requirement or the originating v-fog (12). When the optimal v-fog is found, the MB selects the communication path with the lowest E2E latency between V2V and V2I, before allocating the VM to the optimal v-fog (13). Otherwise, the MB

[2] For instance, if the requesting v-fog belongs to the logical cluster with trust value 7, then only v-fogs in logical clusters with trust value 7 and above are considered for VM allocation.

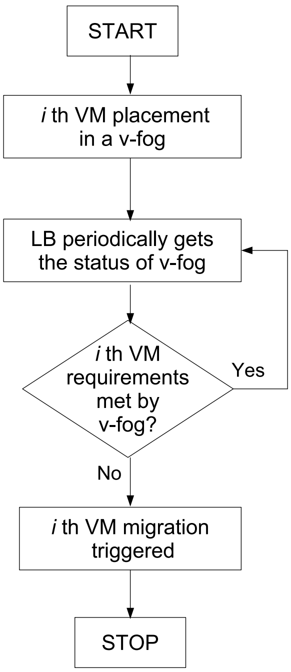


Fig. 6. Flowchart for VM migration trigger algorithm in MB.

proceeds to search the optimal v-fog in the logical clusters in an ascending manner (14) (15). When none of the v-fogs in the logical clusters belonging in that Trust Domain is eligible, the MB continues to search at the next nearby Trust Domain until all the Trust Domains are checked. The request for VM allocation is dropped when no suitable v-fog is found in this option (16) (17).

It is worth noting that as the MB scales out its searching options to find the optimal v-fog, it has a bigger pool of candidate v-fogs for consideration. The whole process is conducted while meeting the VM requirements.

3.3.4. VM migration trigger algorithm

After the MB places *i*th VM to a v-fog, the LB continues to evaluate the status of the v-fog periodically in terms of its trust value and metrics for AHP evaluation in order to track any changes of the v-fog as shown in Fig. 6. When a v-fog's trust value depletes, for instance due to the decrease of security value, or when any of the metrics (i.e. energy consumption, E2E latency, resource availability) that the MB uses in the VM allocation algorithm are less than desirable, such conditions trigger the v-fog to migrate the VM to other v-fog.

4. Performance evaluation

The performance evaluation of the proposed EnTruVe solution is done using Matlab where the number of v-fogs is fixed and each v-fog has a random parking duration throughout the evaluation. The VM allocation request arrival follows the Poisson process where they are processed based on a steady-state First in First Out mechanism. The parameters used in performance analysis are tabulated in Table 2. For the E2E latency, we assume that the range of values is the E2E latency cutoff point i.e. all v-fogs that are considered in the evaluation meets the E2E latency requirement of the VM request. In the VM allocation, three selected metrics from the set M i.e. energy consumption, E2E latency, and resource availability are the criteria chosen for AHP evaluation in order to select the optimal v-fog.

Table 2
Parameters used in performance analysis.

Parameters	Value
β	132.86 mW [50]
Ω^{v}_{max}	1000 MIPS [44]
μ	0.3 tasks/s
EC_{total}	Random, between 1 kJ–100 kJ
L_{e2e}	Random, between 1–30 s
Number of v-fogs	100
Resource availability of a v-fog	Random, between 1%–100%
P_{BB}	0.62 mW [50]
P^{v}_{idle}	6 W [44]
P^{v}_{max}	Random
P_{OH}	Random
P_b	Random, between 0–1
P_l	Random, between 0–1
r	0.08 [43]
Vm	400 MB [6]

A PCM of the criteria, ω is compiled where the matrix's entry represents the importance of a criterion relative to the other criterion. When we set the parameters for this, we assume that E2E latency is 2 times more important than energy consumption because E2E latency is an important factor to consider in 5G and it is 3 times more important than resource availability, and energy consumption has 2 times more importance than resource availability.

We compare our proposed EnTruVe with VaMPIre which is proposed in [35] that closely resembles our work where energy consumption is also considered for their selection criteria. To see how the proposed work performs without considering energy consumption, we revise EnTruVe with the exception of energy consumption as part of AHP evaluation for decision-making and named the solution as TruVe. A random selection solution named as RanSel is also included in this performance evaluation to observe how the random VM allocation performs.

In Section 4.1, we observe the influence of the number of incoming requests on the number of VM migrations, energy efficiency, and utilization of the selected v-fog. Section 4.2 demonstrates the effect of request arrival rate on the number of VM migrations of the three migration options (intra-cluster, inter-cluster and inter-Trust Domain), and the corresponding VM migration energy consumption. Meanwhile, Section 4.3 shows the effect of L_{e2e} (E2E latency) on the number of VM migrations and the maximum utilization of v-fogs.

4.1. Influence of number of incoming requests

As mentioned in Section 1, despite the advantages that virtualization technology can offer to v-fogs, the number of VM migrations between v-fogs can impair the overall system performance. The results in Fig. 7 show how the proposed EnTruVe reduces the number of VM migrations when compared with VaMPIre, TruVe and RanSel, and increases the energy efficiency and utilization based on the number of incoming requests. In this scenario, the number of incoming requests is set from 100 requests, 200 requests, and 300 requests. Fig. 7(a) shows that as the number of incoming requests increases, the number of VM migrations increases, with our EnTruVe having the lowest number of VM migrations of 48 migrations, 80 migrations and 127 migrations when the number of incoming requests are 100 requests, 200 requests, and 300 requests, respectively. This is subsequently followed by VaMPIre, TruVe, and RanSel. This indicates that EnTruVe has the most number of VM allocations without requiring to migrate the VMs after placement. This is because under the proposed EnTruVe, our selection of v-fog that is stable in terms of its availability can completely process the VM requests and is less likely to migrate the VMs elsewhere. This finding highlights the importance of trust-based VM allocation and how the definition of trust stated earlier are reflected in the v-fogs expected behavior.

To show the result in terms of energy efficiency for all of the solutions, Fig. 7(b) is presented where EnTruVe is proven to be more energy-efficient than the rest of the solutions throughout the number of incoming requests of 100 requests, 200 requests, and 300 requests, respectively. The effect of the number of incoming requests on utilization is presented in Fig. 7(c). It shows that as the number of incoming requests increases, v-fog utilization also increases. EnTruVe has the highest utilization from 17% to 57.6% among all solutions and the RanSel solution has the lowest utilization. The obtained results imply the trust-based solution that is offered by EnTruVe reflects the clients expectation of the v-fogs, hence EnTruVe outperforms the other solutions in this subsection.

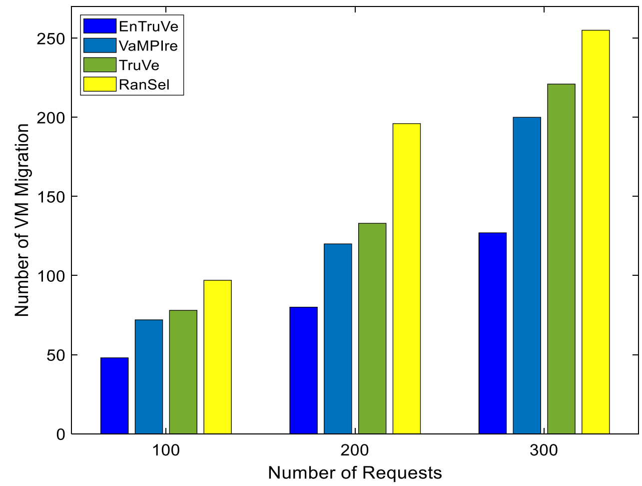
4.2. Influence of VM allocation request arrival rate

The ρ_{max} (v-fog maximum utilization) which is discussed in Section 3.2.2 has an influence on the VM placement, the number of VM placements in a VM placement option, and the subsequent energy consumption of a v-fog associated with this. Fig. 8 shows the proposed three VM allocation options, i.e. intra-cluster, inter-cluster, and inter-Trust Domain for different ρ_{max} values. Fig. 8(a) shows that as the λ increases, and the ρ_{max} increases from 0.2 through 0.6, i.e. E2E latency requirement becomes lenient, we have more VM placement in a particular VM placement option, where we observe 3 VM placements for the top graph, 6 VM placements for the middle graph, and more than 6 VM placements for the bottom graph. These three figures also demonstrate that when ρ_{max} value is small, EnTruVe triggers more than one VM placement option. That is, when $\rho_{max} = 0.2$, it triggers intra-cluster, inter-cluster, and inter-Trust Domain VM placement. When $\rho_{max} = 0.4$, it triggers intra-cluster and inter-cluster migration VM placement. However, when $\rho_{max} = 0.6$, EnTruVe only uses the intra-cluster VM allocation option. This is because the intra-cluster VM placement option has more room to accommodate and process the VM placement request arrival while still adhering to L_{e2e}. EnTruVe shows desirable performance in all results as it considers multiple factors such as trust and E2E latency as part of the v-fog selection evaluation, unlike the other solutions.

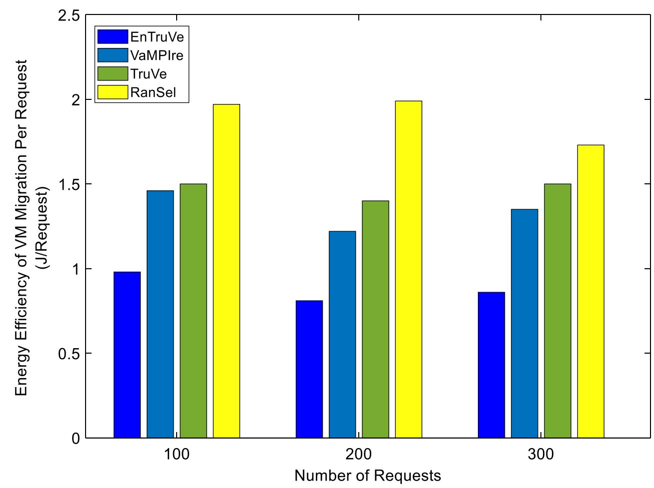
To show the effect of μ of different VM memory size on energy consumption of a v-fog, we compare two VM memory sizes of 200 MB and 400 MB, and μ is set from 5 tasks/s to 50 tasks/s for Fig. 8(b). Fig. 8(b) shows that the energy consumption increases as μ increases. By default, V2V communication first takes place. However, V2I communication takes over when the μ increases from 5 tasks/s to 35 tasks/s. Furthermore, as the VM memory size increases, the energy consumption for VM allocation increases. This occurs due to the increase in number of migration iterations needed for a VM allocation.

4.3. Influence of service latency

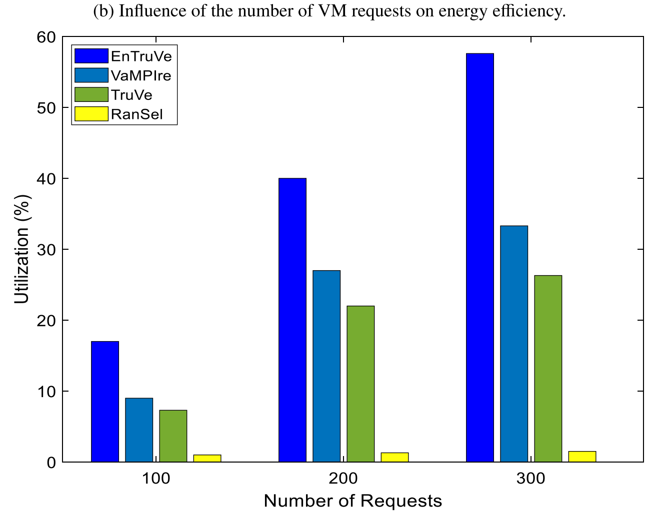
Realizing the importance of L_s (service latency) and L_n (network latency), we show L_s can influence the performance in terms of the number of migrations, and how both L_s and L_n can influence the maximum utilization of a v-fog in our proposed solution. We present the results in Fig. 9(a) where it shows that as L_s increases i.e. becomes lenient, the number of VM migrations decreases as more requests can be accommodated by the selected v-fog. As we can see from this figure, EnTruVe demonstrates the lowest number of VM migrations, followed by TruVe, VaMPIre



(a) Influence of the number of VM requests on number of VM migration.



(b) Influence of the number of VM requests on energy efficiency.

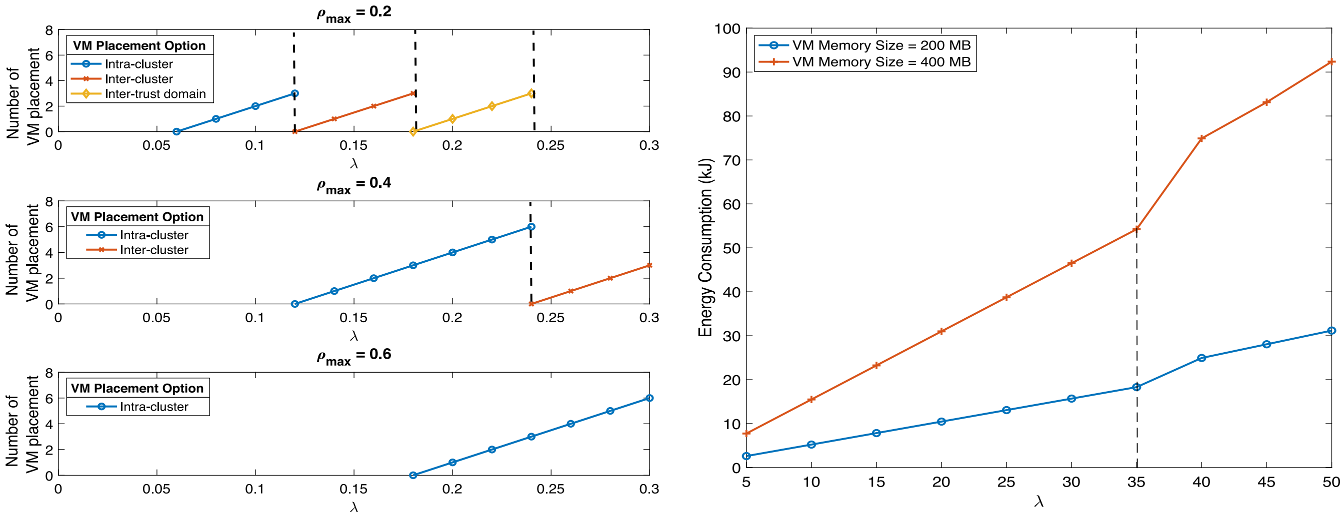


(c) Influence of the number of VM requests on utilization.

Fig. 7. Effect of the number of VM requests on the number of VM migrations, energy efficiency of VM migration, and utilization of v-fog.

and RanSel. This implies that EnTruVe has more successful VM placement among all despite the stringent L_s.

Fig. 9(b) shows the influence of L_s on utilization where as the L_s increases, the maximum utilization that a v-fog can have



(a) Influence of VM request arrival rate and ρ_{max} on the number of VM placements.

(b) Influence of VM request arrival rate on energy consumption.

Fig. 8. Effect of VM request arrival rate on the number of VM placements and energy consumption in a v-fog.

increases. As L_{e2e} is comprised of both L_s and L_n, the bigger the value of L_s results in smaller L_n value that it can tolerate. Fig. 9(c) shows the influence of L_n with $T_{node} = 0$ s and $T_{node} = 3$ s on v-fog maximum utilization (%). As L_n becomes lenient, the maximum utilization that a v-fog can have decreases. This is in line with the result in Fig. 9(a) as the v-fogs have more VMs being placed in the v-fogs. It can be observed that when $T_{node} = 3$ s, the v-fog in EnTruVe solution experience lower maximum utilization with a maximum of 88% compared to when $T_{node} = 0$ s with a maximum of 85%. This indicates that as the T_{node} increases, it can reduce the maximum utilization of a v-fog. Furthermore, the results demonstrate that as L_s increases, the v-fog utilization increases. However, as L_n increases, the v-fog utilization decreases.

5. Discussions

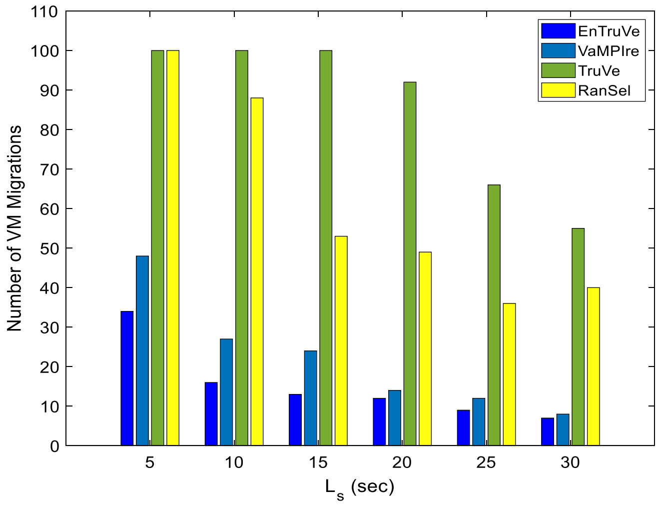
It is apparent that reducing E2E latency is important in VM allocation when 5G is involved. One aspect that can contribute to the E2E latency reduction is minimizing the VM allocation time. However, minimizing the VM allocation time without compromising client requirements is challenging, especially considering the v-fog nature. Furthermore, VM memory can reach gigabytes in size which can increase the E2E latency. Thus, ways to minimize the VM allocation time aside from data deduplication and VM synthesis [5] can be employed. VMs running certain services that the clients are frequently requesting can be pre-cached in the edge, so that the VMs do not have to be acquired from the VMR in the cloud whenever a VM allocation request comes.

As client requests in VFC vary with different geo-spatial conditions, the proposed solution should be able to adjust to the dynamic environment. Artificial Intelligence (AI) can be used in 5G systems to support several applications such as anomaly detection in mobile and wireless networks and provide proactive resource allocation to the clients. Apart from that, using AI through machine learning can help predict the future of incoming client requests based on the previous request arrivals. Another aspect to be considered is on optimizing the relative importance of criterion for the PCM. This is because the judgments using Saaty's scale for PCM highly influences the outcome of v-fog selection, where different criterion importance results in different v-fog selection. Hence, this implies the subjectivity of judgments that are determined based on a defined objective.

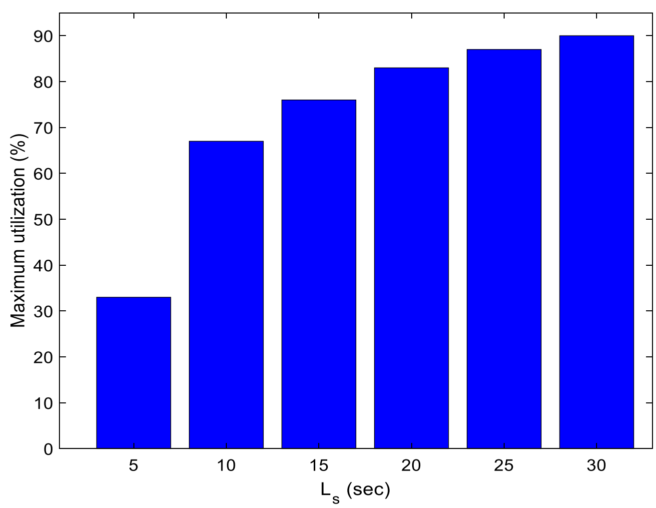
On the other hand, aside from v-fog trust, trust can be observed in various perspectives. Network communication trust is imperative in ensuring a good end-to-end performance. A compromised or untrustworthy network communication can disrupt the VFC services although the v-fogs involved are trusted. For example, a malicious insider might tamper or redirect the communication between two trusted v-fogs, leading to inaccurate v-fog evaluation. Apart from the network communication trust, data trust is another type of trust that can be further studied. Ensuring data trust is especially useful in broadcasting safety messages in ITS where the sender is unknown and v-fog trust is not in place. Not only will the false messages cause unwanted incidents to the v-fogs and the drivers, they can also hinder seamless ITS operations.

6. Conclusions

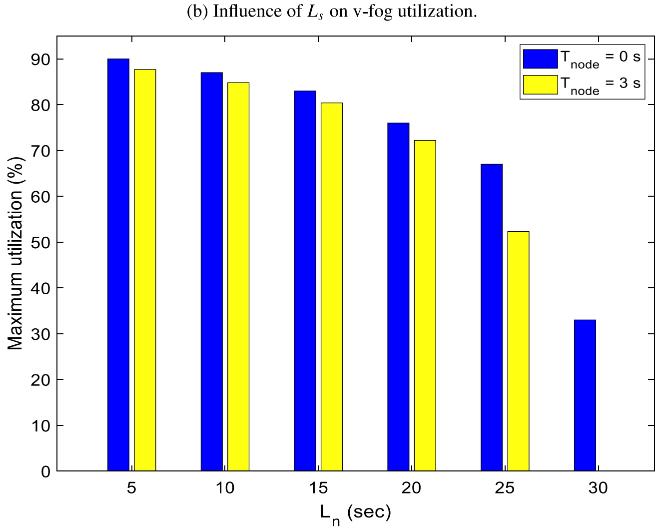
Virtualization technology has proven beneficial in enabling resources to be utilized efficiently in fog computing and it is employed in v-fogs to help support 5G. As VM migrations can impose unnecessary resource consumption, VM migrations should be reduced. However, trust is needed in ensuring seamless VM migrations between v-fogs and it is lacking in the existing studies of vehicular networks. In this study, we have proposed EnTruVe, a first effort in deciding the optimal v-fog for VM allocation with trust taken into consideration. Unlike the existing works, the proposed work has demonstrated that the number of VM migrations can be reduced when VM allocation is carefully decided. We proposed three VM allocation options namely intra-cluster, inter-cluster, and inter-Trust Domain, that can reduce the chances of dropped VM allocation requests while meeting the VM request requirements, i.e. trust, E2E latency requirement and task completion time. We have compared our work with three other solutions namely VaMPIre, TruVe and RanSel. Results from the performance comparison have shown that EnTruVe outperforms the other solutions. Additionally, EnTruVe obtains the highest v-fog utilization and energy efficiency in comparison to other solutions. In the future, we will study the issues such as reducing VM placement time, that we have highlighted in the discussion section of this paper.



(a) Influence of L_s on the number of VM migration.



(b) Influence of L_s on v-fog utilization.



(c) Influence of L_n on v-fog utilization.

Fig. 9. Effect of L_s on the number of VM migrations, and effect of L_s and L_n on utilization.

CRediT authorship contribution statement

Fatin Hamadah Rahman: Conceived the original idea, Algorithm development, Writing the manuscript, Literature review, Mathematical modelling, Simulation programming, Carry out numerical simulation. **S.H. Shah Newaz:** Conceptualization, Writing the manuscript, Mathematical modelling, Proof reading. **Thien-Wan Au:** Literature review, Mathematical modelling, Proof reading. **Wida Susanty Suhaili:** Drawings figures, Processed experimental data, Took part in carry out numerical simulation. **M.A. Parvez Mahmud:** Mathematical modelling, Proof reading. **Gyu Myoung Lee:** Interpreting the results, Supported to identifying the future research issues in this research, Proof reading.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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