A Novel Contract Theory-Based Incentive Mechanism for Cooperative Task-offloading in Vehicular Networks

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Abstract*—Next-generation vehicular networks will impose unprecedented computation demand due to the wide adoption of compute-intensive services such as autonomous driving, in-vehicle infotainment systems, and real-time navigation systems, to name a few. Such services demand computational resources with stringent latency and resource requirements. Vehicular edge or fog computing has been adopted to enhance the computational capacity of vehicular networks; however, the computation, communication, and energy requirements of these applications sometimes surpass the capabilities of edge computing. To address this challenge, the on-board resources of neighboring mobile vehicles can be utilized. However, such resource utilization requires an incentive mechanism to motivate privately owned neighboring vehicles to participate in sharing their resources. To fill the gaps, in this paper, we propose a contract theory-based incentive mechanism to maximize the social welfare of the vehicular networks. The proposed approach enables the Road Side Units (RSUs) to provide appropriate rewards to resource sharing vehicles based on their contribution. This is done by offering a tailored contract for each contributing vehicle based on its unique characteristics. Moreover, we derive an optimal contract scheme for computational task offloading, taking into account the individual rationality and incentive-compatible constraints. Finally, we perform numerical evaluations to demonstrate the effectiveness of our proposed scheme. The proposed scheme achieves up to 29% higher resource utilization, 17% lower energy consumption per resource utilization, and 10% higher number of tasks completed when compared to the linear pricing incentive baseline.

***Index Terms*—Next-generation vehicular network, task offloading, contract theory, vehicle to vehicle resource sharing.**

I. Introduction

Intelligent Transportation System (ITS) realized through connected car technology is poised to transmute the traditional driving experience to a new digital experience. Over the last few decades, the automotive industry in cooperation with tech-giants has been successful in equipping their products with communication, computation, and storage capabilities. As a result, such cars have become a part of the communication eco-system. However, these cars are still resource-constrained for applications that require enormous communication, computation, and storage resources such as autonomous driving. On the other hand, the inception of electrically charged battery-propelled vehicles (Electric Vehicles – EV) instead of fossil fuel-propelled vehicles has considerably contributed to the decrease in carbon emission, footprints and other greenhouse gases that are endangering the environment [1], [2]. Apart from EV, the integration of connected car technology, EV, and autonomous car will be another step towards realizing a futuristic service- and application-rich paradigm [3]. Moving forward, connected car technology (with the add-on of EV and autonomous car) alone cannot complete the smart city eco-system without enabling technologies such as cloud computing and Internet of Things (IoT). In this regard, connected car technology is further extended (from services and applications perspective) to vehicular cloud computing [4], [5] and vehicular social networks [6]. Despite the exciting advancements in these technologies, there are still challenges such as security, privacy, trust, and operational issues that need to be addressed [7], [8]. However, the scope of this work is limited to task offloading and resource utilization. In the following, we discuss the challenges of ITS realized through integrated connected, electric, and autonomous cars.

To this end, connected car technology has the following players: autonomous cars, EVs, fuel-propelled cars, and a combination of these. In EV, although advances in battery technologies have significantly improved but the energy preservation in EVs is still considered as one of the most important challenges [1]–[3]. Moreover, the integration of information and communication technologies to enable futuristic services such as augmented reality [9], infotainment services , and autonomous driving [10], [11] in connected car technology put additional strain of high data communication and computational demands for processing computation-intensive tasks.

For instance, autonomous car performs compute-intensive tasks such as real-time object detection and recognition, route calculation, traffic condition monitoring via communication, and vehicle coordination that result in increased requirements in terms of energy, computation, and communication. One promising approach to alleviate these challenges is to outsource certain resource-hungry tasks and leverage task offloading where a car can offload some of its tasks to nearby devices (that could be another car or a Base Station – BS) that are not resource constrained (neither energy-constrained

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nor computation resource-constrained).

Task offloading is a key feature in the cloud computing paradigm to successfully support resource-constrained devices [12]. However, this approach suffers from the inherent high-latency limitation of cloud computing due to long distances between resource-constrained devices and the cloud. In case of connected car technology, mobility of vehicles introduces more challenges for efficient task offloading. One possible solution is the edge computing paradigm in which the computing capability reside in close proximity to end-devices (i.e., cars), thus, offering on-demand computing resources with extremely low-latency [13], [14]. Nevertheless, vehicular networks cover a large geographical area that would require a huge number of edge servers, posing a significant challenge in terms of installation and maintenance cost. Furthermore, the opportunistic and intermittent nature of vehicular networks will result in huge resource wastage especially in off-peak hours. To alleviate this problem, task offloading to nearby vehicles can be an ideal solution to the described challenges. Such offloading reaps a number of benefits including more computational capacity, lower latency, and higher communication efficiency for vehicular networks. In this regard, it is imperative to design efficient offloading solutions taking into account, vehicular mobility, high computational capacity and latency requirements.

The core challenges for vehicle-to-vehicle (V2V) task offloading in a highway scenario include meeting the task's latency requirement and motivating privately owned mobile cars to participate in offering its resources. Meeting the latency requirements becomes increasingly challenging due to vehicular mobility that might result in longer distance between moving cars and eventually result in more resources (energy) required to serve the offloaded task. Moreover, additional resource overheads such as communication channel utilization might incur, which if not handled properly, might hinder the performance in terms of latency of the offloaded task. Furthermore, the serving cars also have resource constraints in terms of additional energy, communication, and computation power that cannot be shared unconditionally. Similarly, serving other cars would incur further computation overhead due to task processing in terms of its own resources (i.e., consumed computation and communication power) that require compensation by the vehicular network, otherwise it will be very hard to convince vehicular nodes to participate in the task offloading scheme. Thus, an efficient, viable, and acceptable incentive mechanism is required to motivate vehicular nodes[1] to participate in the task offloading as well as optimize the economical benefit of the vehicular network subject to the latency requirement of each task.

A. Related Works

Task offloading has captivated significant attention in futuristic networks such as smart cities, smart homes, and vehicular networks due to the emergence of novel applications and high computational demands. Several works have been carried out to enhance the task offloading performance in edge computing considering key factors such as fairness among tasks [15], energy optimization [16], etc. In particular, there have been several recent works [17]–[19] that have utilized edge computing paradigm in vehicular networks to achieve fruitful performance gains. For instance, in [17], the authors solved a mixed-integer linear programming problem to optimize the cost of edge computing deployment in a vehicular network coverage area. In [18], the authors proposed a heuristic energy-efficient task scheduling approach for edge computing in vehicular networks. Edge computing has also been proposed to enable infotainment services in vehicular networks. In this context, an optimization-based solution to minimize the task latency in vehicular networks for joint communication, caching, and computational problems, has been proposed in [19]. Indeed, edge computing for vehicular networks has enhanced the network performance as evident from the aforementioned works; however, the exponential growth of smart vehicles with increasing task offloading requirement will strain the edge computing capacities and increase the network cost due to massive installation of edge computing servers to meet the next-generation vehicular network requirements. To alleviate this problem, one possible solution is to employ the strong on-board computing resources of the vehicles via V2V communication for task offloading. This phenomenon is also referred to as vehicular Fog to meet the next generation vehicular network requirements.

Leveraging on-board vehicular resources for task offloading have been studied in [20]–[25]. In [20], the authors exploited the vehicular resources to provide a collaborative task offloading mechanism to minimize the latency of the task. Similarly, the work in [21] proposed Fog Following Me (Folo), a solution by utilizing the vehicular resources to achieve a latency bound solution. Similarly, in [22], the authors proposed an efficient task offloading solution to enhance the quality of experience for its users by utilizing vehicular resources. Although these works significantly improved the task offloading mechanism. The principal assumption is that vehicular resources can be utilized unconditionally and these works did not consider any consent from the vehicle owners. Depending on the owner of the vehicle, both consent and motivation for using vehicular resources are essential. To this end, an incentive is the only solution to motivate owners to rent out the resources of their vehicles. An interesting incentive-based task offloading scheme based on the Stackelberg game has been proposed in [23] that uses parked vehicle resources to run distributed compute-intensive applications with the help of a sub-gradient-based iterative algorithm. Similarly, the work in [24] also proposed a multi-level offloading scheme using a Stackelberg game to maximize the benefits for both the vehicles and the edge servers. In [25], another Stackelberg game-based incentive scheme has been devised for task offloading in which the resources of parked vehicles are utilized to maximize the benefits of RSU, parked vehicles, and serving vehicles. Typically in the Stackelberg game framework, a leader has perfect information of follower's strategy leading to a scenario

[1]We want to clarify that we use the terms 'cars', 'vehicular nodes', and 'vehicles' interchangeably and they represent vehicles including EVs, autonomous cars, and normal vehicles, unless specified, otherwise.

of information symmetry. Then, the results of a Stackelberg game are generally obtained by an iterative algorithm requiring several iterations. However, practically the owners of private-owned vehicles are reluctant in revealing their strategies or information due to privacy concerns or other personal factors. Thus, we require incentive mechanisms that can handle the situation of information asymmetry.

To address the challenge of information asymmetry in wireless networks, *contract theory* framework has been adopted to design an effective incentive mechanism [26]. Zhang et al. [27] proposed efficient computation offloading strategies using contract theory that reduces latency and transmission cost for task offloading in vehicular networks. They further extended their work by prioritizing the offloaded tasks [28]. Similarly in [29], the authors used the integration of contract and matching theories to devise and solve the resource allocation and task assignment issues in vehicular fog networks. Similarly, in [30], the authors proposed the integration of learning with contract theory to enhance the task offloading performance in vehicular networks. In all the aforementioned contract-based task offloading schemes, task offloading in a mobile environment does not take mobility into account which is the pinnacle of vehicular networks. In practice, mobility can significantly hinder the overall performance of the task offloaded. Therefore, a mobility-aware design of a contract-based incentive scheme is essential in vehicular networks. Furthermore, the incentive mechanism should be able to address the energy efficiency aspect, especially in electric vehicles as executing tasks would consume energy and this accounts for the most important parameter in task offloading in vehicular networks. In [31], an effective solution based on an Alternating Direction Method of Multipliers (ADMM) has been proposed to solve the joint task offloading and power control problem in vehicular networks. However, this approach only allows energy-intensive tasks to be offloaded to the edge as opposed to offloading to other vehicles. Another notable tasks-offloading solution to assist energy-constrained vehicles is the introduction of Unmanned Aerial Vehicles (UAVs) to assist edge computing servers [32]. However, this type of solution increases the cost of the network.

In summary, none of the aforementioned solutions consider the incentive-based task offloading approach for practical mobile environments with information asymmetric scenarios. Setting out incentivizing measures in terms of task offloading will motivate private-owned cars to participate and result in a huge resource capacity for vehicular networks. This will result in unlocking the full potential of novel resource-hungry services in next-generation vehicular networks.

B. Contributions and Organizations

Motivated by the aforementioned challenges, in this work, we design an incentive mechanism to enable task offloading in vehicular networks subject to energy, computation, and communication constraints. Designing an effective incentive mechanism demands that the incentives or rewards are paid to the participating nodes based on their contributions, i.e., participant that contribute more in the offloading must be rewarded more and vice-versa. Moreover, privately-owned cars will act selfishly claiming high preference towards contribution to harness maximum reward from the incentive mechanism. This becomes challenging for the incentive mechanism designer (i.e., RSU) to design an effective incentive mechanism because of the lack of a prior information that is only available locally at each participating car (i.e., information asymmetry). To this end, we propose a contract theory-based framework and design the task offloading incentive mechanism under information asymmetry. Contract theory framework from microeconomics enables to capture the interactions between the employers and employees in which the skill-set of the later are unknown in advance (i.e., information asymmetry). In our task offloading scenario in vehicular networks, the RSU acts as the employer and offers a bundle of contracts to resource sharing cars (i.e., employees) whose preference is unknown. Each car then chooses a contract that maximizes its utility for performing the task. The contract offered by the RSU represents the reward offered to the participating car for providing its resources (for instance computation and energy resources) to perform the task. Although the preference of participating car in unknown at the RSU side, it has prior knowledge about the evaluation function (preference), an example would be that the evaluation function is strictly concave and has non-decreasing nature. This information is used by the RSU in designing the contract for the incentive calculation. The benefits of using contract theory in our scenario enable us, i) to handle the information asymmetry scenario by allowing self-revealing contract that is primarily important for multi-owner markets (i.e., private-owned cars) where information sharing between owners raise privacy and security concerns, ii) to have a distributed control in which the task offloading is only monitored by the RSU instead of optimization-based approaches in which the RSU has to carry out all operations in a centralized way, and iii) to devise optimal contract thereby maximizing the benefits in terms of utilities both for RSU and the participating cars. Our main contributions of this work are summarized below.

- We propose a novel system model where cars in vehicular networks perform task offloading under the information asymmetry condition. Then, we formulate an optimization problem for task offloading aiming at maximizing the social welfare capturing the utilities of both the RSU and cars. The formulated problem turns out to have a very large size of constraints and obtaining an optimal solution for such a large size is extremely difficult for practical settings.
- Then, we propose an equivalent problem with reduced constraint size. Finally, we propose an optimal contract-based incentive scheme for task offloading based on individual rationality and incentive-compatible constraints.
- We carry out numerical analysis and obtain results to validate the superiority of our proposal under different scenarios and show that the proposed contract-theoretic model can guarantee that the participating cars receive positive payoffs and compatible incentives. Moreover, the proposed scheme achieves up to 29% higher resource utilization, 17% lower energy consumption per resource

utilization, and 10% higher number of tasks completed when compared to the linear pricing incentive baseline.

The rest of this paper is organized as follows. Section II presents the system model of this paper and Section III describes in detail the contract-theory based problem modelling followed by its solution in Section IV. In SectionV, we present the analysis of the numerical results to validate the performance of our proposed solution. Finally, conclusions are drawn in Section VI.

II. System Model and Problem Formulation

Fig. 1 illustrates our system model in which a vehicular network consisting of a single Road Side Unit (RSU) equipped with a Multi-access Edge Computing (MEC) server is considered. The RSU is responsible for assigning resources, its coordination, and task assignment to a set of EVs. These EVs are distributed using the Homogeneous Poisson Point Process (HPPP) under the RSU service radius R. Moreover, we assume that the RSU has prior knowledge from the previous time slot pertaining to EV pairs that can support each other in the offloading process. Multiple approaches such as matching games [29], learning-based clustering approaches [33] can be adopted through which the best EVs pairs can be formed based on parameters such as EVs distance, energy, etc.

In this paper we consider a set $N = \{1, 2, \ldots, N\}$ pairs of EVs. For each $i \in N$, let $i_{SE} \in i$ be the source EV (SE) that requests for offloading service to perform a task and let $i_{DE} \in i$ be the destination EV (DE) that has available resources to assist the RSU for serving the task of this SE. The task profile of an SE i_{SE} is given by $o_i = \{s_i, c_i, e_i\}$, where s_i represents the size of task (bits), c_i is the number of CPU cycles required to process a bit of data of the task, and e_i represents the worst case execution threshold (i.e., latency threshold) for the task of SE i_{SE}. Moreover, we consider a scenario[2] in which these EVs drive on a freeway or highway following the same direction.

In this study, we consider three stages in the offloading process. In the first stage, the SE has to transfer the input data of the task to DE, i.e., o_i. In the second stage, the DE processes the task o_i according to SE's requirement. In the third stage, the DE sends back the result(s) to the SE. These three stages are dependent and related to each other, if any of the stages fails then the offloading process also fails. Therefore, to successfully offload we have to guarantee the completion of all stages. Next, we present the mobility model along with their communication and computation models in the subsequent subsections.

A. Vehicle Mobility Model

In this paper, we consider that both SE, and DE pair i are travelling from their initial position $x_i^{SE}(t_0)$ and $x_i^{DE}(t_0)$ at time t_0 with velocity $v_i^{SE}(t_0)$ and $v_i^{DE}(t_0)$, respectively. Similarly, the acceleration at time t_0 of both SE, and DE pair i is represented by $a_i^{SE}(t_0)$ and $a_i^{DE}(t_0)$, respectively. Since both EVs are moving with non-negative velocities, thus, to measure the distance between each other at any time t, we use the linear motion of relative acceleration between SE and DE pair i represented by $\triangle a_i$. Then, based on the notion of relative acceleration $\triangle a_i$, we can observe whether or not SE and DE pair i is able to use V2V communication. Formally, $\triangle a_i$ is calculated using the kinematic equation as follows:

$$\begin{aligned} a_i^{SE}(t_0) &= \lim_{t \to t_0} \frac{|v_i^{SE}(t) - v_i^{SE}(t_0)|}{t - t_0}, \\ a_i^{DE}(t_0) &= \lim_{t \to t_0} \frac{|v_i^{DE}(t) - v_i^{DE}(t_0)|}{t - t_0}, \\ \triangle a_i(t_0) &= |a_i^{DE}(t_0) - a_i^{SE}(t_0)|. \end{aligned} \tag{1}$$

Note that relative acceleration between SE and DE might lead to a problem of task interruption due to the difference in acceleration between the SE and DE after some time. The

[2]In this study, we consider that all EVs are associated with a single RSU, and challenges stemming from multi-RSU settings such as hand-off, task division and etc. would be subject to our future work.

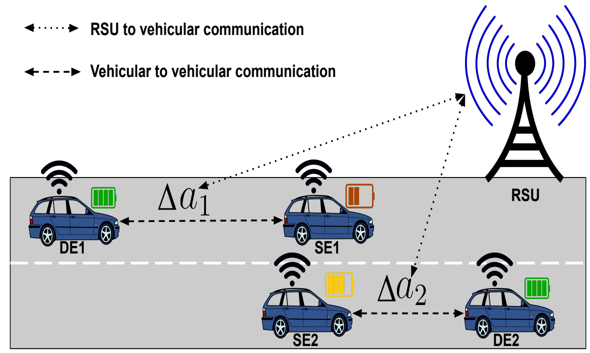


Fig. 1: Vehicle Assisted Task Offloading.

TABLE I: Summary of the key notations.

Notation	Definition
$\mathcal{N}$	Set of pairs of EVs
i_{SE}	Source EV
i_{DE}	Destination EV
o_i	Task profile
s_i	Size of task
c_i	Number of required CPU cycles
e_i	Execution threshold
$x_i^{SE}(t_0)$	Initial position of SE at time t_0
$x_i^{DE}(t_0)$	Initial position of DE at time t_0
$v_i^{SE}(t_0)$	Velocity of SE at time t_0
$v_i^{DE}(t_0)$	Velocity of DE at time t_0
$a_i^{SE}(t_0)$	Acceleration of SE at time t_0
$a_i^{DE}(t_0)$	Acceleration of DE at time t_0
$\triangle a_i$	Relative acceleration
d_i	Distance at time t
r_i^{UL}	Uplink data rate of pair i
r_i^{DL}	Downlink data rate of pair i
p_i^{UL}	Uplink transmission power of pair i
p_i^{DL}	Downlink transmission power of pair i
g_i^{UL}	Uplink channel gain of pair i
g_i^{DL}	Downlink channel gain of pair i
I_0	Additive White Gaussian Noise (AWGN)
W	System bandwidth
h_i	Total CPU cycles of DE to process the task of SE
l_i^{exe}	Execution delay
l_i^{UL}	Uplink delay
l_i^{DL}	Downlink delay
τ_i	Execution threshold
κ	Constant of energy consumption

relative acceleration will define the distance after the time interval $\triangle t = t - t_0$ between both SE and DE if it is too large during the interval, the distance between two EVs might violate the acceptable range d_{max} for V2V communication. Thus, interpreting the task offloading mechanism. An offloading process is completed if and only if after UL and EXE step, SE and DE pair i is still able to communicate with each other or exist within the acceptable range of V2V communication. Therefore, we need to calculate the distance $d_i(t)$ at time instant t. As the EVs are mobile with their respective velocities and acceleration, the distance between SE and DE might vary based on their relative acceleration $\triangle a_i$. Then, $d_i(t)$ can be calculated using the following sequence of kinematics equation:

$$
\begin{aligned}
x_i^{SE}(t) &= \int_{t_0}^{t} \left(v_i^{SE}(t_0) + a_i^{SE}(x)x\right) \partial x, \\
x_i^{DE}(t) &= \int_{t_0}^{t} \left(v_i^{DE}(t_0) + a_i^{DE}(x)x\right) \partial x, \\
\Rightarrow d_i(t) &= \triangle v_i(t_0)t + \frac{1}{2}\triangle a_i(t)t^2.
\end{aligned} \tag{2}
$$

On the other hand, the RSU is only aware of the current velocity of the SE-DE pair at time t_0, and is unable to determine the SE-DE pair's velocities for any future t time slot. Therefore, it is hard to find the distance between two vehicles. One viable option for the RSU to observe this information would be if both SE and DE synchronously increase or decrease its acceleration, thereby enabling the offloading process to be done within the duration of $\triangle t$. However, in reality, each EV's behavior is independent and different from other EVs, thus, this observation is not applicable. This leads to the problem of interruption of the offloaded process. To enable such an option, the RSU has to offer a reward to motivate EVs to synchronously increase or decrease its acceleration with respect to each other during the offloading process. Then, the goal is to enable an incentive-based task offloading mechanism between these mobile EVs with the collaboration of the RSU. Next subsection, we define the communication and computation model for the proposed incentive-based offloading scheme.

B. Communication Model

In this section, we present our communication model. In the model, we choose a Long-Term Evolution (LTE) and Fifth Generation (5G) based technologies opposed to the Dedicated Short-range Communications (DSRC)/IEEE802.11p technologies for communication modeling as the LTE provides a higher channel bandwidth compared to the DSRC which is more suitable for task offloading in vehicular networks. For these LTE merits, the proposed solution is based on it [29], [34]. However, the methodology developed in this paper can be applied to the DSRC based technologies as well. In order to enable communication in any pair of EVs, we need to calculate the achievable rate between them under both scenarios UL and DL. Let r_i^{UL} represent the achievable data rate (i.e., UL step communication) of SE-DE pair i at time t_0 which can be calculated as follows:

$$
r_i^{UL} = W(t_0)\log_2\left(1 + \frac{p_i^{UL} g_i^{UL} d_i(t_0)^{-\alpha}}{I + N_0}\right), \tag{3}
$$

where $W(t_0)$ is the system bandwidth at the time t_0, p_i^{UL} represents the transmit power of SE i_{SE}, g_i^{UL} is the channel gain of between SE-DE pair i and $d_i(t_0)$ represents the distance between SE-DE pair i, where α represents the path loss exponent. We use the slow-flat Rayleigh fading to deal with the small scale fading, where its channel gain is assumed to be exponentially distributed with unit mean [35]. $I = \sum_{i' \in N \setminus i} p_{i'}^{UL} g_{i'}^{UL} d_{i'}(t_0)^{-\alpha}$ represents the interference from all other i' V2V pairs and N_0 represents the Additive White Gaussian Noise (AWGN).

Note that we have considered that RSU allocates orthogonal resource blocks for enabling the V2V communication. Thus, we assume no inter resource blocks interference in this work and would be a subject for future studies. Similarly, the DL achievable data rate between DE and SE pair i after time $t = t_0 + \triangle t$ is represented by $r_i^{DL}(t)$ as follows:

$$
r_i^{DL} = W(t)\log_2\left(1 + \frac{p_i^{DL} g_i^{DL} d_i(t)^{-\alpha}}{I + N_0}\right). \tag{4}
$$

Based on (3), and (4), we can calculate the UL and DL delay as following:

$$
l_i^{UL} = s_i / r_i^{UL}, \tag{5}
$$

$$
l_i^{DL} = s_i^{out} / r_i^{DL}, \tag{6}
$$

where s_i is the task size as input to the DE and s_i^{out} represents the result in terms of size of the computational task after the execution step. Moreover, the transmit power for DL and UL is calculated as:

$$
p_i^{UL} = \frac{I_0}{g_i^{UL} d_i(t_0)^{-\alpha}}\left(2^{r_i^{UL}/W(t_0)} - 1\right), \tag{7}
$$

$$
p_i^{DL} = \frac{I_0}{g_i^{DL} d_i(t)^{-\alpha}}\left(2^{r_i^{UL}/W(t)} - 1\right). \tag{8}
$$

Next, we present our computation model.

C. Computation Model

In this section, we present our computational resource allocation model. To find the required computational resource for executing a task, we need to calculate the total delay for executing the task. Therefore, we first calculate the delay required to execute the offloaded task from SE to DE. Given the size of offloading task s_i, the processing or execution delay (i.e., l_i^{exe}) can be calculated as follows:

$$
l_i^{exe} = c_i s_i / h_i, \tag{9}
$$

where h_i is the total CPU cycles allocated by DE to process the task of SE. According to the delay constraint e_i, the offloading task must be completed within the time threshold executing all the three steps, i.e., UL, DL, and EXE steps. Let $\triangle t_i$ be the time that SE-DE pair i requires to execute these steps, then, the following constraint requires to be satisfied for the successful execution of the task offloading:

$$l_i^{UL} + l_i^{DL} + l_i^{exe} \leq \tau_i = \min\{e_i, \triangle t_i\}, \forall i \in N. \quad (10)$$

Based on (10), we can measurement the total required computational resource in terms of computation cycles h_i by the DE i_{DE} to execute the task of SE i_{SE} given as follows:

$$h_i \geq \frac{s_i c_i}{\tau_i - l_i^{UL} - l_i^{DL}}, \forall i \in N. \quad (11)$$

Note that from (11), a DE can measure the number of computation cycles it has to provide for successful task execution subject to the task's execution threshold τ_i by taking the inequality to be the equality constraint. Thus, we can observe the correlation between computational resource requirement and relative acceleration from (10) and (11). It can be inferred that if the relative acceleration between the SE and DE is higher, more computation resources need to be provided by the DE to abide by the task's execution threshold τ_i. In the next subsection, we define the utility function of our offloading problem in mobile V2V networks.

D. Utility modeling and Task Offloading challenges

First, we model the utility of our approach under the energy consumption with respect to the quality of service (QoS) of the task. In this paper, we consider the energy efficiency problem, hence, we formulate our utility function under energy consumption as following:

$$E(i) = p_i^{UL} s_i / r_i^{UL} + p_i^{DL} s_i^{out} / r_i^{DL} + \kappa (h_i)^2 s_i, \forall i \in N, \quad (12)$$

where κ is a constant of energy consumption that depends on the CPU architecture. In order to utilize DE resources, the RSU has to pay an incentive amount to the DE proportional with its effort in task offloading services.

Then, the objective of our task offloading problem would be to minimize the utility given in (12) subject to the minimum required computational resource given in (11) and worst-case latency threshold for each offloaded task i provided in (10). Moreover, the problem also needs to capture the relative acceleration bounded by the maximum V2V communication range given as follows:

$$\triangle a_i \leq \frac{2 d_{max}}{\tau_i^2}. \quad (13)$$

Note that minimizing the utility of the task offloading problem in highly mobile V2V networks is not a trivial task subject to the aforementioned constraints. The main challenges are the coupling stemming from the minimum required computational resource given in (11) and un-observable values of relative acceleration $\triangle a_i$ given in (13) due to the lack of prior knowledge. Thus, it is extremely hard to obtain an optimal solution for the task offloading problem without significant message passing overhead. For instance, the RSU needs information pertaining to SE and DE real-time locations, current accelerations, DEs' computational resources and etc. to compute the feasibility of task offloading between the SE-DE pair. Thus, given the tight latency constraint and highly mobile V2V networks obtaining an optimal solution for such a problem becomes intractable for a practical setting of vehicular networks using traditional optimization based approaches. Moreover, another challenge would be motivating private-owned DEs to contribute towards offloading service by providing them with appropriate incentives or rewards and ensuring that private owned DEs do not act selfishly by not revealing its true local capabilities which can result in degrading of the offloading services. This reflects the information asymmetry challenge in which the RSU is unaware of DE's local state and capabilities.

Therefore, we propose a solution approach based on the framework of contract theory through which we can handle the aforementioned challenges of un-observable values and information asymmetry, i.e., lack of prior information (local DE information). Moreover, adopting this approach enables us to make the relative acceleration $\triangle a_i$ observable which results in obtaining the distance between the SE-DE pair after time $\triangle t$. Consequently, then the coupling constraint in (11) can be relaxed as $l_i^{UL}, l_i^{DL}, l_i^{exe}$ is separately observable.

III. Contract Theory Based Model for Task Offloading

In this section, we model our task offloading problem using the contract theory framework and propose a contract based incentive mechanism for task offloading in mobile V2V networks. In the following subsections, first, we model the different types of EVs[3] that exist in our model. Second, we introduce the utilities of both the participating DEs and the RSU followed by the introduction of the social welfare for the task offloading problem.

The goal of this work is to design an incentive approach that aims to maximize the utility of both the DEs and the RSU. As stated in the previous section, we have N pair of SE-DE denoted as $\mathcal{N} = \{1, 2, \ldots, N\}$, in which, each DE has heterogeneous capabilities: computational capacity, acceleration, energy, etc. Then, to enable the V2V offloading service, the RSU has to specify a bundle of contract $\{U[(\theta)], R(\theta)\}$. Where $R(\theta)$ is the payoff or reward given to the DE at type θ for using its resources and $U[(\theta)]$ represents the expected benefit gained by the RSU for the type θ. Note that it is assumed that the function $U[(\theta)]$ is strictly increasing function with respect to θ, which infers that a DE who provides more expected benefit value to RSU will get more reward. Next, we design the contract types based on different DE types in our system.

A. DE Vehicle Types

In this subsection, we define the DE types available in our system. The types of DEs are defined based on their effort to contribute to the task offloading service. Thus, if DE has spent a higher effort in the system it is given more reward and has a higher type compared to DE putting a lower effort.

In our work, we define the availability of a DE i_{DE} to perform task offloading based on the relative acceleration with

[3]In this study, we base our analysis on the DE as it is sharing its resources and acting as an employee.

respect to SE i_{SE}. Thus, the type of each DE depends on its acceleration relative to SE. Let us assume a set of DE belongs to a group type θ if and only if it has a relative acceleration of $\triangle a_\theta$ with respect to an SE. Since the behavior of DE is unpredictable, and has different acceleration representing its type, therefore, this information is unknown to the RSU. Thus, it cannot measures the availability of DE for any SE after $\triangle t$ time slots. However, under information asymmetry condition, the only information available at RSU is the probability density function (PDF) $f(\theta)$ on a continuous interval $[\underline{\theta}, \overline{\theta}]$. Thus, the RSU is then required to design multiple contracts for all types starting from the minimum ($\underline{\theta}$) to maximum ($\overline{\theta}$) relative acceleration represented by the continuous interval $[\underline{\theta}, \overline{\theta}]$. Note that the maximum relative acceleration threshold can be calculated by setting an acceptable communication distance between SE-DE pairs (i.e., $d_{\max}$). As we have a set of SEs in our network that requires offloading services, then, for each SE $i_{SE} \in i$, the RSU will offer a contract bundle $\big[U(i,\theta), R(i,\theta)\big]$. However, it is assumed that each SE-DE pair i task is identically independent with each other, then, we can analyze for a single task and apply the analysis for the whole system. Thus, we simplify the contract bundle as $\big[U(\theta), R(\theta)\big]$, where $U(\theta)$ is a utility function for any given task of SE-DE pair i at type-θ, and $R(\theta)$ is the reward associate with $U(\theta)$.

Definition 1. The type of DEs are sorted in ascending order

$$0 < \underline{\theta} < \ldots < \theta < \ldots < \overline{\theta}, \tag{14}$$

The type of DE depends upon the relative acceleration with respect to the SE. If relative acceleration is small, it will be associated with a lower type, and vice versa.

Based on the type of DE, the RSU will offer a contract to a DE. The DE can either choose to participate or reject the contract offered based on its local or private information. In case of DE declining to participate, we can assume that a DE has signed a contract of $\big[U(0), R(0)\big]$, $U(0) = 0$, representing the DE and RSU will be awarded $R(0) = U[R(0)] = 0$ utility. Next, we define the RSU and DEs utilities for designing the contract in our model.

B. RSU Utility

The utility function of the RSU to offload the SE's task is linear to its task size. Then, the utility of the RSU for offloading o_i at θ be represented as:

$$U_{RSU}(\theta) = U(\theta) - \gamma R(\theta), \tag{15}$$

where $R(\theta)$ is the incentive RSU has to pay to the DE with type θ to process the task and γ represents the unit cost of the effort paid by the RSU. $U(\theta)$ represents the expected utility benefit achieved by the RSU by utilizing the resource of DE at type θ. In this work, we use (12) as the utility U. Moreover, it can be seen from (15) that it is beneficial for an RSU to enable V2V communication between the SE-DE pair only if the $U(\theta) - \gamma R(\theta) > 0$. As there are infinite number of DE types represented by the contracts ranging from the interval $[\underline{\theta}, \overline{\theta}]$ of RSU for any given SE-DE pair's i task, then, the expected utility of the RSU can be calculated as follows:

$$U_{RSU} = \int_{\underline{\theta}}^{\overline{\theta}} U_{RSU}(\theta) f(\theta) d\theta. \tag{16}$$

C. DE Utility

The utility of any DE with type-θ associated with a bundle of contract $\big[U(\theta), R(\theta)\big]$ is denoted as:

$$U_{DE}(\theta) = \theta\nu\left(R(\theta)\right) - \rho U(\theta) \tag{17}$$

where $\nu(\cdot)$ is the self evaluation function of the DE, which is strictly concave, increasing function of $R(\theta)$, where $\partial\nu\left[R(\theta)\right]/\partial R(\theta) > 0$ and $\partial^2\nu\left[R(\theta)\right]/\partial R(\theta)^2 < 0$. ρ represents the unit cost of effort put in by the DE according to the expected utility U. This can be represented as additional power or energy consumed by the DE to process the computation task of SE. Given the above information, DE needs to choose the bundle of contract that maximizes its utility.

D. Social Welfare

In this subsection, we design the social welfare of our incentive-based proposed approach. Social welfare is defined by the summation of the RSU and DEs utilities. In our work, there are N SE-DE pairs that are involved in the offloading of tasks, each choosing a contract bundle associated with type θ from the continuous range $[\underline{\theta}, \overline{\theta}]$. Then, the social welfare can be defined as the summation of both the RSU and DEs utilities as follows:

$$\begin{aligned}\Gamma &= \int_{\underline{\theta}}^{\overline{\theta}} \left(U_{RSU}(\theta) + U_{DE}(\theta)\right) f(\theta) d\theta, \\ &= \int_{\underline{\theta}}^{\overline{\theta}} \Big(\theta\nu\left(R(\theta)\right) - \gamma R(\theta)\Big) f(\theta) d\theta.\end{aligned} \tag{18}$$

The aim of this work is to maximize the social welfare of the network for the task offloading problem which implicitly maximizes the utilities of both the RSU and the DEs.

IV. Proposed Approach

In this section, we present the solution to the task offloading problem in V2V networks. First, the necessary conditions are derived to achieve a contract followed by the formulation of the contract based optimization problem to handle the offloading problem. Finally, we present the proposed solution of the optimization problem to obtain the optimal contracts.

A. Contract Feasible Conditions

In this subsection, we discuss the contract feasibility conditions. A contract is considered feasible if and only if two conditions are held, i.e., Individual Rationality (IR) and Individual Compatibility (IC).

Definition 2. Individual Rationality (IR): *The utility of a DE participating in any feasible contract bundle* $\left[U\left(\theta\right), R(\theta)\right]$ *must be non-negative,*

$$U_{DE}(\theta) = \theta\nu(R\left(\theta\right)) - U\left(\theta\right) \geq 0. \tag{19}$$

The IR constraint ensures that a DE that offers its offloading services achieves a benefit that motivates DEs' participation in the offloading scheme. If $U_{DE}(\theta) \leq 0$, the DE will not accept the contract as it is not beneficial for it. Next, we discuss the second basic property for the contract feasibility, i.e., incentive compatibility. It is important that once a contract bundle is offered by the RSU, the DE of type θ chooses the contract designed only for its type, i.e., (type θ). This is ensured by the incentive compatibility constraint as follows:

Definition 3. Incentive Compatible (IC): *A DE must prefer the contract designed for its type θ among the offered contract bundle*

$$\begin{aligned} \theta\nu(R\left(\theta\right)) - U\left(\theta\right) > \theta\nu(R\left(\theta\right)') - U\left(\theta'\right), \\ \forall\theta, \theta' \in [\underline{\theta}, \overline{\theta}]. \end{aligned} \tag{20}$$

This property of contact theory ensures that a DE always chooses the correct type to maximize its utility. Otherwise, it will be penalized for choosing the wrong type. This property ensures private owned selfish DE's to choose the correct type to maximize their benefit. Next, we define an additional condition for the reward function in the contract theory framework, i.e., the monotonicity condition. This condition ensures that the DE with a higher type receives more reward as it would contribute more in the task offloading. Formally, stated as:

Definition 4. *Monotonicity: Given any task of SE-DE pair $i \in N$, for any feasible contract bundle $\left[U\left(\theta\right), R(\theta)\right]$, the reward function must satisfy the following condition,*

$$0 = R(0) < R(\underline{\theta}) < \ldots < R(\theta) < \ldots < R(\overline{\theta}). \tag{21}$$

It is equivalent to stating that if DE spends more effort in the offloading service it will get more benefit compared to any DE that spends less effort.

In summary, these aforementioned conditions ensure that DEs processing any task of SE i_{SE} with type θ receives a non-negative benefit, maximizes its utility by choosing the correct type of contract among all types, and a DE that participates more resources in the task offloading service receives more benefit when compared to less participating EVs.

B. Problem Formulation

Given the feasibility conditions for contract design, we formulate the task offloading problem with an objective to maximize the social welfare of the network as follows:

$$\max_{U(\theta), R(\theta)} \int_{\underline{\theta}}^{\overline{\theta}} \Big(\theta\nu\left(R(\theta)\right) - \gamma R(\theta)\Big) f(\theta) d\theta \tag{22a}$$

s.t.

$$\text{C1}: \theta\nu[R(\theta)] - U(\theta) \geq 0, \tag{22b}$$

$$\text{C2}: \theta\nu(\theta) - U\left(\theta\right) > \theta\nu(\theta') - U\left(\theta'\right), \tag{22c}$$

$$\begin{aligned} \text{C3}: 0 = R(0) < R(\underline{\theta}) < \ldots < R(\overline{\theta}), \\ \forall\theta, \theta' \in [\underline{\theta}, \overline{\theta}]. \end{aligned} \tag{22d}$$

The constrain (C1) represents the IR constraint, and the IC constraint is represented by (C2). Moreover, for simplicity, we denote $\nu(R\left(\theta\right))$ as $\nu(\theta)$. The constrain (C3) represents the monotonicity condition ensuring the reward function which is an increasing function of θ. Note that the problem (22) has a very large size due to constraints (C1) (i.e., $|[\underline{\theta}, \overline{\theta}]|$) and (C2) (i.e., $|[\underline{\theta}, \overline{\theta}]| \times |[\underline{\theta}, \overline{\theta}]| - 1$). Thus, finding a solution for such large scale problems for a practical settings is intractable or time consuming which cannot be applied for practical mobile V2V networks due to stringent delay requirements and highly dynamic nature. Therefore, in order to solve this problem, we need to reduce the size of the problem. This is done by reducing the number of constraints in the problem. Therefore, to reduce the size, we do the following scaling of IC and IR constraints:

Lemma 1. Local Downward Incentive Constrains (LDICs): *For any feasible contract bundle $\left[U\left(\theta\right), R(\theta)\right]$, the following condition will be held:*

$$\begin{aligned} \theta\nu(\theta) - U\left(\theta\right) \geq \theta\nu(\underline{\theta}) - U\left(\underline{\theta}\right), \\ \overline{\theta} \geq \theta > \underline{\theta} \geq 0. \end{aligned} \tag{23}$$

if and only if

$$\theta\nu(\theta) - U\left(\theta\right) > \theta\nu(\theta - \xi) - U\left(\theta - \xi\right), \tag{24}$$

where ξ represents any positive number, i.e. $\xi > 0$.

Proof: We can observe from the IC constraint that:

$$\begin{aligned} \theta_1\nu(\theta_1) - U\left(\theta_1\right) > \theta_1\nu(\theta_2) - U\left(\theta_2\right), \\ \theta_2\nu(\theta_2) - U\left(\theta_2\right) > \theta_2\nu(\theta_1) - U\left(\theta_1\right), \end{aligned} \tag{25}$$

where $\theta_1, \theta_2 \in [\underline{\theta}, \overline{\theta}]$, $\theta_1 < \theta_2$. Then, based on (12) and strictly concave function property of $\nu(\cdot)$, it can be observed that the equality only occurs if and only if $\theta_1 = \theta_2$. When $\theta_1 \neq \theta_2$, after some manipulations, we can achieve the following:

$$\nu(\theta_1)\left(\theta_1 - \theta_2\right) > \nu(\theta_2)\left(\theta_1 - \theta_2\right) \tag{26}$$

Then, we divide both sides of inequality with the term $(\theta_1 - \theta_2)$, since $\theta_1 < \theta_2$, we get $\nu(\theta_2) > \nu(\theta_1)$. Thus, for any given $\theta > \hat{\theta} = \theta - \xi > \underline{\theta}$, we have:

$$\theta\left(\nu(\theta) - \nu(\hat{\theta})\right) \geq \hat{\theta}\left(\nu(\theta) - \nu(\hat{\theta})\right). \tag{27}$$

On the other hand, $\nu(\cdot)$ is a strictly concave function, increasing function of $R(\theta)$. Moreover, note that if $\nu(\theta) \geq \nu(\hat{\theta})$, then $U_{DE}(\theta) \geq U_{DE}(\hat{\theta})$ must also hold. Then, using the property of IR constraints, without loss generality, we can approximate

$\nu(\theta)$ by $U(\theta)$, and $\nu(\hat{\theta})$ by $U(\hat{\theta})$, respectively. Hence, we can rewrite (27) by the following:

$$\theta\left(\nu(\theta)-\nu(\hat{\theta})\right) \geq U(\theta)-U(\hat{\theta}) \tag{28}$$

From (27), and (28) we can express as follows:

$$\begin{aligned} \theta\nu(\theta) - U(\theta) &\geq \theta\nu(\hat{\theta}) - U(\hat{\theta}), \\ &\geq \dots, \\ &\geq \theta\nu(\underline{\theta}) - U(\underline{\theta}). \end{aligned} \tag{29}$$

This means that if the LDIC between adjacent types hold, then all LDICs hold automatically. Hence, we have completed the proof for LDICs. ■

Lemma 2. Local Upward Incentive Constrains (LUICs): *For any feasible contract bundle* $\left[U(\theta), R(\theta)\right]$*, the following will be held:*

$$\begin{aligned} \theta\nu(\theta) - U(\theta) &\geq \theta\nu(\overline{\theta}) - U(\overline{\theta}), \\ 0 < \underline{\theta} &\leq \theta \leq \overline{\theta}. \end{aligned} \tag{30}$$

if and only if,

$$\theta\nu(\theta) - U(\theta) \geq \theta\nu(\theta+\xi) - U(\theta+\xi), \tag{31}$$

where ξ *represents any small positive number, i.e.,* $\xi > 0$*.*

Proof: Similar to the proof of Lemma. 1. For given any $\theta < \hat{\theta} = \theta + \xi > \underline{\theta}$, we have :

$$\begin{aligned} \theta\nu(\theta) - U(\theta) &\geq \theta\nu(\hat{\theta}) - U(\hat{\theta}), \\ &\geq \dots, \\ &\geq \theta\nu(\overline{\theta}) - U(\overline{\theta}). \end{aligned} \tag{32}$$

Thus, we complete the proof for LUICs. ■

Lemma 3. IR constraints reduction: *The number IR constraints will be held if and only if*

$$\underline{\theta}\nu(\underline{\theta}) - U(\underline{\theta}) \geq 0. \tag{33}$$

Proof: Based on (26), (28), and Monotonicity of U, we can easily see that

$$\begin{aligned} \overline{\theta}\nu(\overline{\theta}) - U(\overline{\theta}) &\geq \theta\nu(\theta) - U(\theta), \\ &\geq \dots, \\ &\geq \underline{\theta}\nu(\underline{\theta}) - U(\underline{\theta}). \end{aligned} \tag{34}$$

Therefore, total number of $|[\underline{\theta}, \overline{\theta}]|$ can be reduced into a single constraint (33). It means if the utility of the lowest type is satisfied, the entirety of the constraint set will hold. ■

C. Optimal Contract Design

Based on the aforementioned lemmas and feasible conditions, we can rewrite the reduced problem of (22) as an equivalent problem as follows:

$$\max_{U(\theta),R(\theta)} \int_{\underline{\theta}}^{\overline{\theta}} \left(\theta\nu\left(R(\theta)\right) - \gamma R(\theta)\right) f(\theta) d\theta, \tag{35a}$$

s.t.

$$\text{C1}: \underline{\theta}\nu[R(\underline{\theta})] - U(\underline{\theta}) \geq 0, \tag{35b}$$

$$\text{C2}: \theta\nu(\theta) - U(\theta) \geq \theta\nu(\theta+\xi) - U(\theta+\xi), \tag{35c}$$

$$\text{C3}: \theta\nu(\theta) - U(\theta) \geq \theta\nu(\theta-\xi) - U(\theta-\xi), \tag{35d}$$

$$\text{C4}: 0 = R(0) < R(\underline{\theta}) < \dots R(\theta) \dots < R(\overline{\theta}), \tag{35e}$$

$$\forall \theta, \theta' \in [\underline{\theta}, \overline{\theta}], \forall \xi \geq 0.$$

Since the number of IR and IC constraint are now reduced. The problem in (35) can be solved by using the Lagrangian multiplier method by relaxing the constraint (C4). This can be considered as a projection function that can capture the feasibility of the solutions [36]. The pseudo-code for the contract based incentive scheme for task offloading in mobile V2V networks is presented in Algo. 1.

D. Practical Implementation

The Algo. 1 starts by initializing the parameters as inputs (line 1). Once the RSU receives requests from SEs regarding the task, the RSU needs to check if there are some potential DE in the range of the requesting SE to which the task can be offloaded. After receiving this information regarding the SE-DE pairs, the RSU will inform the DEs regarding the the task profile $o_i = \{s_i, c_i, e_i\}, \forall i \in N$ by using the broadcast channel. Then, all vehicles will calculate its effort for serving the task via Eq. (7, 8, 11, 9), simultaneously. Note that the task's payload consists of 3 real values in which each value can be represented by 4 bytes [37], thus, 12 bytes of overhead in total to execute this step. Then, the RSU solves the problem stated in (35) to calculate the optimal contract and inform this information to the candidate DE (lines 3-4). This will incur an overhead in which the payload would be $4 \times 2 \times T$ bytes for each contract bundle (i.e., contract type, reward value). Moreover, it will also calculate the initial inter SE-DE pair distance d_i (line 5). If d_i turns out to be greater than the maximum V2V range d_{max}, then, the RSU will not offer the contract and will serve the request itself (lines 6-7). Otherwise, the RSU will inform the contract bundles to the candidate DE along with information regarding the task profile, SE's position, and its acceleration (lines 8-9). Note that, if the relative acceleration between SE and DE is high, the inter SE-DE distance can violate the maximum V2V limit threshold d_{max}. Based on these pieces of information, the DE will estimate the effort required to serve the task and evaluate the contract (line 10). After the evaluation of the contract by the DE in terms of its utility, it will send feedback (i.e., payload of 4 bytes which contains only the contract type) to the RSU making a decision to either accept or reject the contract based on its local information (lines 11-17). After getting the feedback from DE in case of DE's rejection, RSU serves the request. Otherwise, the RSU will sign the contract with the DE that has accepted for offering the offloading

Algorithm 1 Optimal Contract based Task Offloading

1: **Input:** $\underline{\theta}, \overline{\theta}, f(\theta), \mathbf{v}, \gamma, o_i = \{s_i, c_i, e_i\}, \forall i \in N$
2: **Output:** $\big[U((\cdot)), R(\cdot)\big]$
3: Task offloading request, $\forall i \in N$;
4: **Optimal Contract:** Solve problem in (35);
5: RSU calculates $d_i = \sqrt{(x_i^{SE})^2 - (x_i^{DE})^2}$;
6: **if** $d_i \geq d_{max}$ **then**
7: RSU serves the request with $\big[U(0), R(0)\big]$;
8: **else**
9: RSU broadcasts contract bundle $[U(\theta), R(\theta)]$, o_i, x_i^{SE}, and a_i^{SE} to candidate DE;
10: DE estimate effort based on information via (17);
11: **if** $U_{DE} > 0$ **then**
12: DE accepts and sends feedback;
13: **else**
14: DE rejects and sends feedback;
15: RSU serves the request with $\big[U(0), R(0)\big]$;
16: **end if**
17: **end if**
18: **Contract Execution:**
19: RSU establishes SE-DE connection for accepted pairs;
20: **if** $l_i^{UL} + l_i^{DL} + l_i^{exe} \leq \tau_i$ **then**
21: DE receives $R(\theta)$ as committed in contract;
22: **else**
23: RSU serves the request with $\big[U(0), R(0)\big]$;
24: **end if**

services. Then, the RSU will inform the respective SEs to be served by the employed DEs (i.e., the overhead would be the input data of the task transmitted to the DE with payload of $s_i, \forall i \in N$ bytes.) that have signed the contract with the RSU for task offloading resulting in task execution. Note that the SE and DE will then set up a V2V link for task offloading under the supervision of the RSU by sending control signals, and also receiving feedback signals from the V2V pair (i.e., RSU provides communication channels) (lines 18-19). If the task offloading process is performed successfully (i.e., the overhead would be the output of task o_i represented as $s_i' \leq s_i$ bytes), the RSU rewards the DE as agreed by the contract (line 21), otherwise, no reward is given and the RSU serves the task request (line 23). Next, we evaluate the computational complexity of the proposed approach. Note that we need to calculate the complexity based on the problem (i.e., (35)) that is solved in line 4 of Algo. 1. As the number of EV pairs are N in our system, thus, the overall complexity of our proposed Algo. 1 is $\mathcal{O}(N \times M \log(M))$ based on finding a solution for a convex problem as stated in (35) [38]. However, our proposed model assumes independent tasks, then, the RSU can solve this problem in a parallel manner for each SE-DE pair. Then, we can claim that our proposed algorithm has a computational complexity of $\mathcal{O}(M \log(M))$ which is polynomial with respect to feasible set of θ and shows reasonable performance for practical implementation.

V. Numerical Results

In this section, we present our numerical results to validate the proposed scheme through simulations. In the following subsections, first, we present the simulation setup and the parameters used in our simulation. Second, we present the contract feasibility conditions for the proposed incentive scheme based on the optimal contract for task offloading in mobile V2V networks. Finally, we investigate the system performance of the proposed scheme by varying various parameters to analyze its results.

TABLE II: Simulation parameters [29], [35]

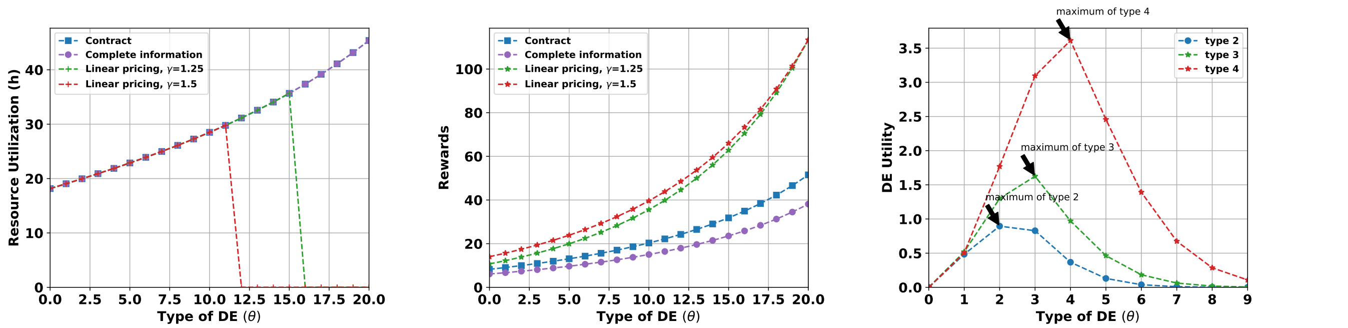
Simulation Parameters	Values
Radius of RSU	500 m
Number of vehicles	20
Task data size	$100-200$ Mb
Task computation size	$100-400$ Mb
Task deadline	$1-5$ s
Bandwidth of EV	$20\,\text{MHz}$
Transmission power of EV	$23\,\text{dBm}$
Communication range of EV	$100\,\text{m}$
Noise Power	$-174\,\text{dBm}$
Path loss exponent	4

A. Simulation Setup

We assume a single RSU scenario installed at a fixed location providing a coverage range of 500m to $N = 20$ SE-DE pairs deployed randomly following a homogeneous Poisson point process (PPP) under its coverage, wherein each pair represents a task to be offloaded. The inter SE-DE distance between each pair is chosen based on uniform distribution ranging from $[20-200]\text{m}$. Each SE and DE pair i is travelling in a uniform direction with constant acceleration ranging from $[0-20]\text{m/s}$. For simplicity, it is assumed that DE has enough resources to fulfill these requirements given the optimal incentives provided. Furthermore, the main parameters used in our simulations are shown in Table. II unless stated otherwise. Note that, all statistical results are averaged over large runs of random locations of SE-DE pairs and task profiles.

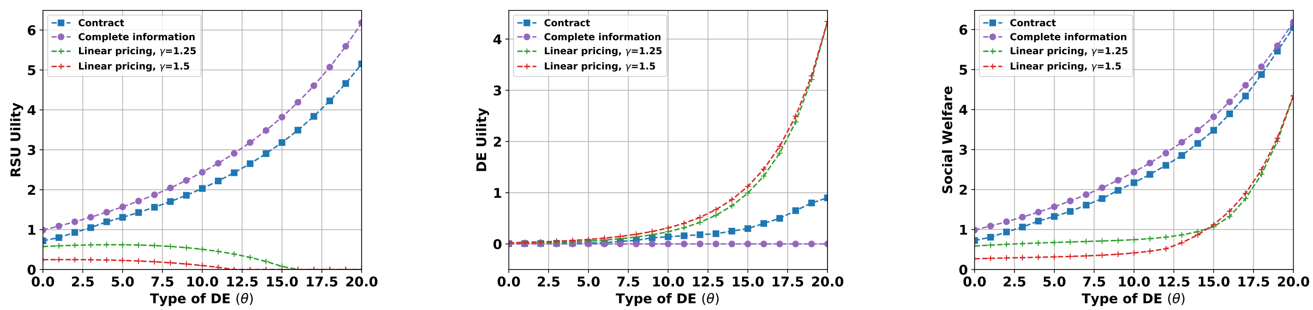
B. Contract Feasibility

We conduct a series of simulations to present the contract feasibility for the proposed incentive-based task offloading scheme. We validate the conditions of incentive compatibility and monotonicity presented in Definition 3 and 4, respectively. In Fig. 2, we present the contract feasibility conditions for the contract. In this simulation, we consider a network with $N = 20$ SE-DE pairs each accelerating in the range of $[0-20]$ m/s, where the task profile of each SE is considered fixed with task size of 100 Mb and task deadline of 2 s. To draw comparisons against the proposed scheme, we introduce two baseline schemes, first, the "Linear Pricing" scheme also adopted by the works in [36] as a baseline incentive scheme for the domain of enabling underlaid device to device communication in the cellular network. In this scheme, the RSU pays a unit price of γ per resource utilization as an incentive proposed by the DE for using its resources. We choose two unit prices, i.e, $\gamma = 1.25$ and $\gamma = 1.5$ for this simulation to analyze the effect of prices. Note that, this incentive-based scheme also falls under the category of information asymmetry, i.e.,



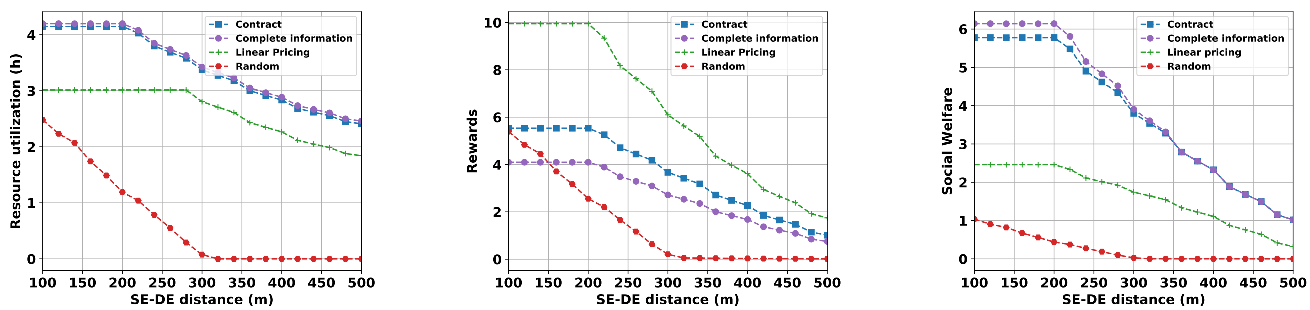
(a) Resource Utilization (b) Reward (c) DE Utility

Fig. 2: Contract feasibility conditions (a) Resource utilization, (b) Reward (c) DE utility.



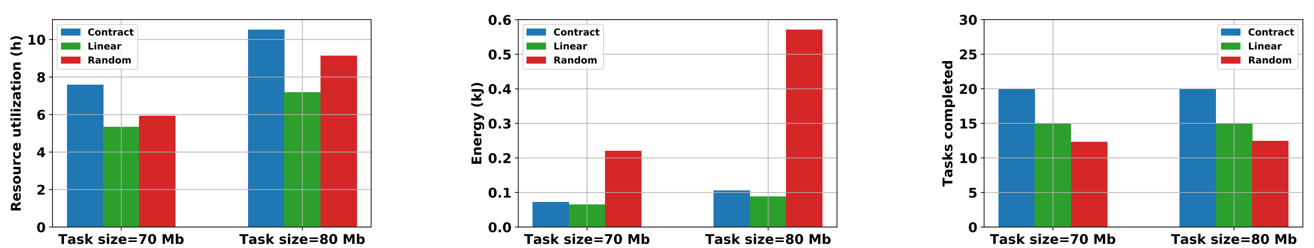
(a) RSU Utility (b) DE Utility (c) Social Welfare

Fig. 3: System performance with respect to different DE Type (a) RSU utility (b) DE utility (c) Social welfare.



(a) Resource Utilization (b) Reward (c) Social Welfare

Fig. 4: System performance with respect to inter SE-DE distance (a) Resource utilization (b) Rewards (c) Social welfare.



(a) Resource Utilization (b) Energy Consumption (c) Task Offloaded

Fig. 5: System performance comparison in terms of (a) Average Resource utilization (b) Average energy consumption (c) Average task offloaded.

RSU has no acknowledgment of the DE type. The second scheme, namely “Complete Information” is a scheme that employs contract with complete knowledge of DE types. In this scheme, the RSU acts selfishly and increases its profit by offering all DEs the minimum reward (i.e., meeting the IR constraint). Moreover, in this study, we assume that the task is non-divisible and cannot be performed based on the available resources.

Fig. 2a and 2b presents the DEs’ resource utilization and its reward to validate the monotonicity condition of the proposed scheme. It can be seen that the resource utilization and reward increase with respect to the DE type which is consistent with our model, which has been already presented in (21). Moreover, we observe that in Fig. 2a, a sudden drop for the linear pricing scheme once the type of DE(i.e., relative acceleration) exceeds a certain threshold, i.e., type 12.5 and type 16 for prices $\gamma = 1.25$ and $\gamma = 1.5$, respectively. The main reason behind this trend is that as relative acceleration increases, more resources are required by the DE and it demands more reward, thereby reducing the RSU’s utility until achieving zero utility. It can also be seen that once the price per resource utilization is reduced by the DE, more resources are utilized. Fig. 2b also follows this trend in which the reward is a strictly increasing function of the DE type that follows the property of monotonicity.

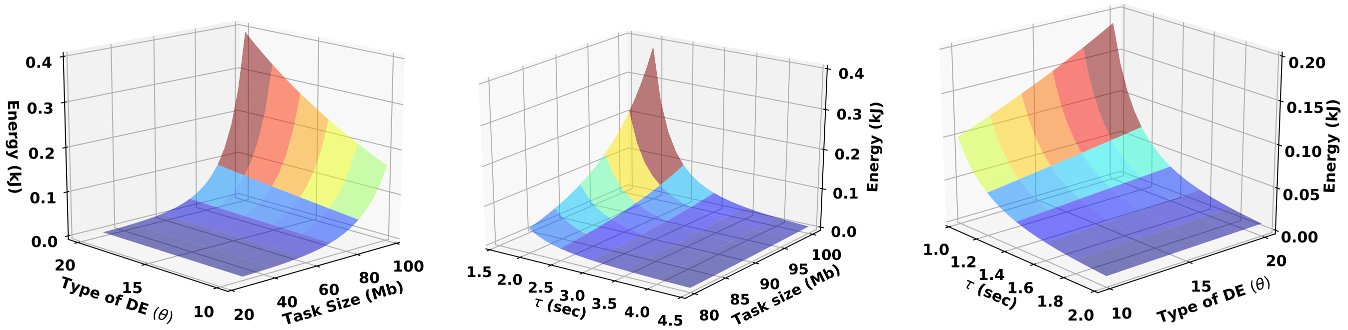
Fig. 2c shows the utilities of DE with type $2,\ 3$, and 4 for all contracts offered by the RSU. We can infer that the maximum utility of a DE can only be achieved if it selects the contract based on its type and will be penalized if it selects any other contract which corroborates with the incentive compatibility condition presented in Definition 3 as well as Lemma 1 and Lemma 2. Moreover, this also allows the RSU to automatically identify the DE type once the contract is accepted by the DE. Furthermore, numerical results provide evidence that DE’s of higher type will have a higher utility when compared to lower type, i.e. $U_{DE}(2) < U_{DE}(3) < U_{DE}(4)$ which agrees with the analysis of the proposed contract design.

C. System Performance

We evaluate the performance of our incentive-based scheme by varying different parameters to analyze their impact. In Fig 3, we evaluate the utilities of RSU, DE, and present social welfare with respect to varying DE types. We can observe that as the DE type increases the utilities of RSU and DE increase, resulting in higher social welfare. Moreover, we observe that the proposed approach outperforms the linear pricing scheme in terms of BS utility (i.e., Fig. 3a) and social welfare (i.e., Fig. 3c). The main reason behind this is that in linear pricing mechanism the DE sets a price per computational resource to maximize its benefit (i.e., Fig. 3b) without considering anything else. Once the relative acceleration increases, i.e, type of DE, the DE needs more resources that will increase its price. On the other hand, the RSU is unaware of its type and will only accept DE’s offloading services for prices that result in a positive utility. This is also evident from Fig. 3b in which once the DE demands higher prices, the RSU rejects the offers, thereby resulting in a lower RSU utility and overall social welfare.

Fig. 4 presents the average resource utilization, average reward, and average social welfare with respect to the inter SE-DE distance. We run this simulation with the same parameters but relax the task deadline threshold to 5 s to evaluate the effect as inter SE-DE pair distance increases. Moreover, we use the linear pricing scheme with a price $\gamma = 1.25$ for all further simulations and introduce a new baseline denoted as the ”Random” scheme. The random scheme also operates under the information asymmetry scenario; however, in this scheme, the DE’s do not take into account the relative acceleration of SE’s during the task offloading service. It can be seen that as the inter SE-DE distance increases the average resource utilization (i.e., Fig. 4a), average reward (i.e., Fig. 4b) and average social welfare (i.e., Fig. 4c) decreases for all schemes. However, the proposed scheme achieves a significantly higher performance compared to the linear pricing and random baseline schemes. For instance, the optimal contract based scheme achieves an average performing gain of up to 29% and 300% when compared with the linear and random baselines respectively in terms of resource utilization. On the other hand, the average social welfare even at an extreme distance of 400 m increases by 90% and 130% when compared to the linear and random baselines, respectively. The reason for performance drop with respect to distance is that higher relative accelerating DEs’ cannot abide by the task offloading threshold (i.e., lines 20-21 of Algo. 1) at larger inter SE-DE distance (i.e., above 350 m for the proposed scheme). Consequently, resulting in incomplete task execution and achieving zero rewards and utility (i.e., lines 22-23 of Algo. 1). On the other hand, DEs with lower relative acceleration maintain almost indistinguishable inter SE-DE distance which results in successful task offloading.

In Fig. 5, we compare average resource utilization (i.e., Fig. 5a), the average energy consumption for the utilized resources (i.e., Fig. 5b), and average number of successful tasks offloaded (i.e., Fig. 5c). In the simulation, we fix the inter SE-DE distance to 100 m for a network with 20 SE-DE pairs and compare the performance with the baselines in terms of average energy consumption per resource utilization for two different task sizes. Fig. 5a presents the average resource utilization for all schemes. We infer that the optimal contract-based schemes utilize the resources most efficiently under both task sizes compared to the baselines. In Fig. 5b, we compute the average energy required by all schemes to perform these tasks. It can be seen that the proposed contract based approach achieves a significantly higher energy efficiency per resource utilization by controlling DE’s acceleration relative to SE. This approach allows the DE to use its computational resources efficiently and reduces the downlink transmission energy; whereas, in the random baseline, the energy efficiency results are worst as in that case DE’s do not abide by the relative acceleration. For instance, the energy per resource utilization ratio for the proposed scheme to process a task of size 80 Mb is 10.1; whereas, the linear and random baselines perform the same task with ratios of 12.2 and 62.4, respectively. The energy reduction of up to 17.2% and 84% is achieved in terms of energy per resource utilization. In Fig. 5, we see that because of the optimal contract proposed in our approach,



(a) DE type (θ) and task size

(b) Task deadline(τ) and task size

(c) Task deadline(τ) and DE type (θ)

Fig. 6: Average energy consumption of the proposed scheme with varying (a) DE type(θ) and task size (b) Task deadline(τ) and task size (c) Task deadline(τ) and DE type(θ).

the average number of task offloaded and completed are significantly higher compared to both the baselines, thereby resulting in higher SE's satisfaction. Moreover, the energy per task completed using the optimal contract-based scheme is significantly lower in all cases compared to both baselines. For instance, each task requires 3.65J and 4.47J of energy via the contract and linear schemes when task size size is 70 Mb. On the other hand when task size is 80 MB, the energy per task for the proposed and linear scheme is 5.3J and 5.86J respectively. This gives us up to 17.1% and 9.3% lesser energy per task compared to the linear baseline for task sizes of 70 Mb and 80 Mb, respectively. Similarly, 87.4% lesser energy is consumed compared to the random baseline for task size of 80 Mb.

Fig. 6 provides the analysis of energy consumption for the proposed scheme by varying the parameters of task size, type of DE, and deadline threshold (τ). In Fig. 6a, we vary the task size and the type of DE for a network with a fixed task deadline threshold of 2 s to investigate the energy consumption. We observe that energy consumption increases with respect to both the task size and type of DE. This is because as task size increases more computation resources are required as stated in (11) to complete the task resulting in higher energy which corroborates to (12). Additionally, we can infer that as the type of DE values become larger (i.e., a large type of DE value reflects high relative acceleration between the SE-DE pair compared to a lower type of DE) the inter SE-DE distance increases. Then, to ensure the task deadline threshold (i.e., line 20 of Algo.1), DE has to provide more computational resources resulting in an overall increase in energy consumption. Next in Fig. 6b, we vary the parameters of task size and the deadline threshold to investigate the effect of energy. It can be observed that energy increases with an increase in the task size and decreases as the deadline threshold is relaxed. Finally, in Fig. 6c, we vary the deadline threshold and the type of DE for a network with a fixed task size of 80 Mb. The energy consumption increases as the relative acceleration increases similar to the Fig. 6a due to higher inter SE-DE distance. On the other hand, we observe that as the deadline threshold becomes strict, energy consumption increases due to higher resource requirements even at lower acceleration following the trend of Fig. 6b.

VI. Conclusions

In this paper, a task offloading mechanism between moving vehicles has been proposed using a contract-theoretic model through which we motivate vehicles to participate in the offloading process. We use the framework of contract theory to develop a novel self revealing scheme to address the challenge of information asymmetry due to which private information of vehicles is unknown to the road side unit. Numerical results demonstrate the superiority of the proposed incentive-based scheme when compared to the linear pricing and random baselines. Moreover, the results indicate that the proposed approach significantly enhances the overall energy efficiency and computational resource utilization. In future works, we would extend our study by investigating more complicated scenarios by collecting real traces of traffic and extending our solution by incorporating leaning-based approaches.

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