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# Forming Teams of Smart Objects to Support Mobile Edge Computing for IoT-Based Connected Vehicles

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**Abstract**

This paper proposes a collaborative framework to support task offloading in connected vehicular environments. The approach relies on the dynamic formation of temporary teams of connected vehicles in a mobile edge computing scenario. A novel trust model is introduced, which integrates both quality of service and quality of results into a unified reliability score, and combines this score with distributed reputation to build a comprehensive trust metric. This trust metric is then exploited to guide a decentralized team formation algorithm, ensuring lightweight, interpretable, and scalable decision-making processes. Simulation results demonstrate that the proposed framework improves task execution quality and fairness, especially for low-performing vehicles. These contributions highlight the novelty and strengths of our collaborative model, positioning it as a promising solution for enhancing cooperation in vehicular edge systems.

**Keywords:** mobile edge computing; smart objects; Internet of Things; connected vehicles



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## 1. Introduction

Connected vehicles (CVs), namely vehicles equipped with communication, sensing, and computation capabilities, are increasingly present in smart urban mobility ecosystems. CVs enable a variety of services, such as traffic coordination, real-time navigation, and cooperative driving, by interacting with peers, roadside units, and edge infrastructure via the Internet. Among their many benefits, CVs can support task offloading to mobile edge computing (MEC) servers to improve performance indicators such as latency, energy efficiency, and processing time, especially in computationally intensive or time-critical tasks (for instance, [1–3]). Broadly speaking, MEC-assisted CVs reduce the need for onboard computation, while enabling distributed intelligence and improved quality of service (QoS). In particular, CVs represent a critical enabling technology for Intelligent Transportation Systems (ITS), especially when involved in collaborative offloading strategies. In this perspective, the formation of temporary, cooperative teams of heterogeneous CVs emerges as a key advancement within the broader context of vehicles exploiting the opportunities make available from the Internet of Things (IoT) technologies [4].

However, designing effective criteria for team formation among CVs is challenging, due to their high mobility, heterogeneity (in terms of capabilities, energy constraints, and connectivity), and the dynamic nature of urban environments. Moreover, the absence of centralized coordination and the scarcity of historical data further complicate team

orchestration. Rather than relying solely on structural or functional similarities among vehicles, one promising approach is to exploit social properties—such as experience, reliability, and interaction history—to maximize the probability of forming effective collaborations.

While several trust and reputation systems have been proposed for vehicular networks, most existing approaches still face critical limitations when applied to highly dynamic and heterogeneous urban environments. In particular, centralized models often suffer from scalability and single failure points, whereas decentralized methods typically rely on static or narrowly defined trust indicators, limiting their adaptability to different offloading contexts. Furthermore, many existing frameworks mainly emphasize either objective Quality of Service (QoS) metrics or past reputation, without adequately integrating subjective Quality of Results (QoR) into the trust assessment. These gaps hinder the formation of effective, reliable, and context-aware collaborations among vehicles. To address these shortcomings, our work introduces a novel framework that integrates both QoS- and QoR-based reliability with distributed reputation sharing, thereby providing a more comprehensive and flexible trust mechanism to support team formation in MEC-assisted vehicular networks.

The study of the behaviour of connected vehicles when supported by a mobile edge computing scenario is interesting for a few reasons. First of all, CVs can generate large volumes of data. Moreover, many CV applications require timely processing: for instance, cooperative perception, real-time navigation, and safety-critical alerts. Since MEC infrastructures can hold significant computation and storage resources closer to vehicles, latency can be significantly reduced. Moreover, such computations will not overload centralized cloud servers. Last but not least, such a combined approach can ensure scalability in dense traffic environments. Therefore, the integration of CVs with MEC represents a good example of efficient task offloading in order to support the development of intelligent transportation services. For the above reasons, the MEC paradigm provides an excellent context in which to implement collaborative trust and team formation mechanisms for vehicular networks.

### *1.1. Main Contributions*

The relevant contributions of this work can be summarized as follows:

- **Integrated trust metric:** We propose a trust model specifically designed for task offloading of connected vehicles. In this model we unify *Quality of Service* and *Quality of Results* into a single reliability score, and further combines it with distributed reputation sharing. This multi-dimensional approach captures both objective and subjective performance aspects, overcoming the limitations of existing models that typically focus on only one dimension.
- **Decentralized team formation:** We present the design of a fully distributed algorithm for the dynamic formation of temporary teams of CVs. The algorithm ranks the vehicles according to their trust values, enabling scalable and fault-tolerant cooperation without reliance on centralized authorities. Trust values are computed on the basis of the integrated trust metric mentioned in the previous point.
- **Agent-based modeling of CVs:** Each CV is "agentified" following the principles of Multi-Agent Systems (MAS). This allows vehicles to autonomously evaluate their own trust profiles, reason about peer selection, and engage in collaborative decision-making within the MEC ecosystem.
- **Performance evaluation under heterogeneous conditions:** The framework has been validated through simulations. In particular, we simulated 1000 CVs, multiple task categories, and vehicles with difference performance profiles. The analysis of the results has proved that the proposed trust-based team formation mechanism

makes a significant contribution to improving task execution quality and system responsiveness. In particular, low-performing vehicles benefit from collaborating with more reliable peers.

Overall, this work introduces a comprehensive and practical trust-based collaboration model for MEC-assisted vehicular networks, combining elements that, to the best of our knowledge, have not been jointly addressed in the prior literature.

### 1.2. Main Limitations

As stated above, the approach presented in this work has been validated by proper simulations that allowed us to verify the effectiveness of the trust measure and of the team formation algorithm. We discuss further aspects in the conclusive section concerning the future work, including the introduction of additional contextual parameters necessary to perform effective comparisons with different approaches. In addition to the aspects already mentioned, several other limitations must be acknowledged:

- **Scalability.** While the proposed model has low computational complexity at the level of individual CVs, scalability at city-wide scale could be affected by the number of vehicles simultaneously engaged in team formation. Future work should validate performance in large-scale network simulators to assess this aspect.
- **Communication overhead.** Our model is based on the exchange of reliability information among neighboring CVs which, in turn, represents an additional communication cost. These messages are exchanged during the team formation round; they are represented by repeated broadcasts and may occur also in dense traffic conditions. In this specific condition, these repeated broadcasts may contribute to network congestion. Efficient communication protocols and selective dissemination strategies should be investigated to mitigate this issue.
- **Privacy concerns.** Sharing QoS/QoR evaluations and reliability scores may expose sensitive information about vehicle behavior or user preferences. Privacy-preserving mechanisms (e.g., anonymization, differential privacy, or secure aggregation) will be required to ensure compliance with data protection principles.
- **Vulnerability to collusion.** As in most reputation-based systems, groups of malicious vehicles could collude to artificially inflate trust scores or to discredit honest participants. Detecting and mitigating such collusion attacks represents an important extension, potentially leveraging outlier detection, cryptographic mechanisms, or trust propagation techniques.

Overall, while the proposed framework demonstrates promising results under the presented assumptions, these limitations highlight the need for further validation and enhancements in order to ensure robustness, privacy, and scalability in real-world deployments.

### 1.3. Organization of the Manuscript

The remainder of this paper is organized as follows. Section 2 presents background on connected vehicles, agent-based models, and trust mechanisms in MEC. Section 3 introduces our reference scenario. Section 4 details the trust model used for evaluating and selecting CVs and our team formation algorithm. Section 5 reports on the experimental evaluation and performance analysis. Finally, Section 6 concludes the paper and outlines future research directions.

## 2. Background and Related Work

Mobile urban networks offer several advantages to users moving in urban traffic, including connectivity with points of interest, personal devices, cloud platforms, and travel

routes. As a result, trips can be adapted to dynamic traffic conditions in order to optimize traffic flows with respect to distances, travel time, safety, and unexpected events. To realize such targets, CVs must integrate advanced communication capabilities for exchanging data in real time, both among themselves and with infrastructural elements, by following the concept of Cooperative, Connected, and Automated Mobility (CCAM) [5]. With reference to such a scenario, we mention several progresses obtained in vehicular communication technologies like Vehicle-to-Vehicle (V2V) [6], Vehicle-to-Infrastructure (V2I)) [7], Vehicular Ad-hoc Networks (VANET) [8] or, more generally, V2X Vehicle-to-Everything [9], as well as Wireless Sensor Networks (WSNs) [10].

In the realm of vehicular communications, to realize reliable, safe, and satisfactory CV interactions, a possible solution consists of adopting trust and/or reputation systems to evaluate the trustworthiness of one's own counterpart/s. To this end, we found an overwhelming number of different trust and reputation approaches, each implementing different analyses, architectures, and models, in the current literature [11–16]. Three main aspects contribute to obtain valid trust measures, namely: (i) exploiting an adequate number of reliable sources [17]; (ii) adopting a centralized or distributed system that is well-fitting with the specific context [18]; and (iii) aggregating trust (i.e., reputation) in a local or global modality [19]. Moreover, based on [20], the following properties should also be verified: (i) the consideration that long-life actors have a significant amount of past experiences, such that counterparts' future behaviors can be reliably predicted and whitewashing strategies are more difficult to be enacted; (ii) the performance of a new interaction driven based on past experiences; (iii) granting and spreading trust/reputation measures/feedback in the community (a task that is more complex in distributed than in centralized contexts).

The adoption of a trust or reputation system is also very helpful in the group formation of processes. In fact, such systems can be fundamental in suggesting to a group a potential actor to join with and, vice versa, to an actor an advantageous group to join [21]. By using trust or reputation measures in the group formation process, it has been verified that the resulting groups are more stable over time with respect to other strategies, and interactions occurring therein are more satisfactory [22].

Defined in the contextual framework, the formation of temporary teams of CVs can represent a promising approach to manage traffic and unexpected road events by exchanging information in a quick fashion [23,24]. The basic characteristic denoting such CV teams is in their intrinsically temporary nature, given that CVs can enter and leave a team based on their physical proximity, trajectory, speed, traffic density, common information interests, and other factors, not least of which is individual reputation [25]. In fact, one of the most relevant concern about these CV networks relates to the reliability of shared information, in order to avoid the spreading of false or malicious data. For such a reason, several studies have assumed as a key aspect the introduction of trust and reputation systems to estimate reliability, benevolence, and other aspects to assess the credibility of a source before accepting it as a member of a team [26,27]. Such systems are usually based on historical data sequences, correlation with other independent sources, and direct evaluations provided by other CVs with which interactions occurred in the past.

In this area, the recent studies of Souissi et al. [28] and of Amari et al. [29] have provided a complete analysis about trust management techniques in VANET-based systems, emphasizing how reputation metrics can effectively complement, and sometimes replace, cryptographic approaches to mitigate insider attacks carried out by CVs, which can spread harmful information in order to cause disruption or gain an undue advantage. This can be obtained by adopting centralized or distributed approaches; realization of the first approach is simpler, as it maintains trust scores in a centralized repository, while in the other case, each VC calculates and updates the trust score of other nodes locally.

Another example of temporary CV teams is TRIP, presented in [30], which has been conceived to identify CVs providing false reports by combining data and vehicle reputation. TRIP provides the system with stronger resilience against coordinated attacks and ensures greater information consistency in highly mobile networks, as seen in some simulations that have tested its performance in different operative scenarios. Temporary team formation processes often adopt clustering algorithms to organize CVs in order to increase the group stability. Different clustering techniques for different VANET scenarios are analyzed in [31], which also summarizes existing clustering performance metrics and performance evaluation approaches. Among such clustering techniques, there exist proposals for trust-based clustering algorithms, as in [32], where a Trust-based Stable Clustering (TSC) solution is proposed to build stable clusters in VANETs. TSC allows realization of the cluster head election, cluster joining, and cluster leaving algorithms. Some tests have shown that TSC outperforms the compared competitors.

In addition to the team formation problem, the problem of selecting a leader of a temporary team or a platoon is also often addressed. Moving in a platoon is an usual conditions for CAVs (Connected Automated Vehicles), and describes a situation where multiple vehicles travel together in coordinated formation and form an involuntary temporary group. For instance, in [33], in the presence of a CAV platooning scenario, a trust and privacy-based recommendation scheme called TPPR enables the avoidance of selecting a malicious platoon head. In TPPR, a truth discovery process is performed to calculate the reputation of each vehicle candidate at the platoon leader role. A wide security analysis has been carried out to verify the resilience of TPPR against some sophisticated attacks. Another reputation-based mechanism to elect the platoon leader is presented in [34]. This system consists of two subsystems. The former is characterized to save reputation value on a blockchain; the other one implements an incentive mechanism to stimulate participation om the elections.

The adoption of reputation systems in V2V contexts can also involve traffic management. For example, highly reputed CVs could obtain a priority to disseminate traffic information like congestion situations by reducing the risk that inaccurate data could pose to the route planning of other users [35]. Similarly, reputation scores can be exploited to set the frequency of message transmission in order to minimize network load without affecting information quality [36]. Finally, other application areas includes trust and reputation systems for CVs, proposing emerging technologies such as edge computing and blockchain. Processing at the edge of the network allows trust to be assessed almost in real time, improving both latency and system responsiveness, as in [37]. In addition, the use of blockchain allows the maintenance of reputation records immutably over time, improving transparency and resistance to tampering, as in the above-cited [34].

Another important objective of IoT is the protection of customer privacy, data integrity, and confidentiality, as well as the security of assets and IoT devices and the accessibility of services provided by an IoT ecosystem. In this regard, the IoT must meet user demands while consuming the least number of resources, including money, vitality, and time [38,39]. As for the relationship between MAC and IoT, in [40] the authors investigate a wireless powered mobile edge computing (WP-MEC) network with multiple hybrid access points (HAPs) in a dynamic environment, where wireless devices (WDs) harvest energy from radio frequency (RF) signals of HAPs, and then compute their computation data locally (i.e., local computing mode) or offload it to the chosen HAPs (i.e., edge computing mode).

In summary, (see Table 1), existing approaches to trust and reputation in vehicular networks exhibit several recurring characteristics. Centralized models are easier to implement but suffer from scalability issues and single points of failure [11,18], while decentralized solutions increase robustness but often rely on static or limited trust

indicators [26,27,32]. Some works emphasize only objective QoS metrics (e.g., latency, throughput) [30,31], whereas others mainly focus on historical reputation or clustering strategies [31,34–36]. Few approaches attempt to jointly capture both objective and subjective dimensions of performance in a distributed manner. Compared to these, our framework introduces three main advances: (i) the integration of both QoS and QoR into a unified reliability score, (ii) the combination of this reliability with distributed reputation sharing to build a comprehensive trust metric, and (iii) the use of this trust metric to guide a decentralized team formation algorithm for MEC-assisted vehicular environments. This analytical comparison highlights the novelty of our proposal and clarifies its positioning with respect to the state of the art.

**Table 1.** Comparison of representative trust and reputation approaches in vehicular networks with the proposed framework.

| Approach | Key Characteristics | Main Limitations | Comparison with Our Work |
|---|---|---|---|
| Centralized trust and reputation models [11,18] | Rely on a central authority to store and manage trust scores. | Scalability issues; single point of failure; limited adaptability in dynamic scenarios. | Our framework is fully distributed, avoiding central bottlenecks and enhancing fault tolerance. |
| Decentralized and clustering-based solutions [26,27,32] | Distribute trust computations across vehicles; use clustering to improve stability. | Often rely on static or limited trust indicators; clustering overhead. | We adopt a dynamic trust metric (QoS + QoR + reputation) without fixed cluster structures, enabling higher flexibility. |
| QoS-centric approaches [30,31] | Focus mainly on performance-related indicators such as latency, delay, throughput. | Neglect subjective outcomes or quality of results; vulnerable to incomplete evaluation. | We integrate both objective QoS and subjective QoR into a unified reliability measure. |
| Reputation- or history-based mechanisms [31,33–36] | Base trust on accumulated history and peer ratings; sometimes enhanced by blockchain or incentives. | Require long-term interactions; may be slow to adapt in highly dynamic environments. | Our model combines reputation with immediate reliability (QoS/QoR), achieving faster adaptation in temporary teams. |
| Proposed framework | Integrates QoS and QoR into reliability, combines with distributed reputation, and exploits the resulting trust to drive decentralized team formation. | – | Advances beyond existing works by jointly addressing performance, subjectivity, and scalability in a unified model. |

## 3. Our Scenario

The reference scenario of this work is composed of a certain number of CVs [41] moving in a given geographic area, for instance a metropolitan area, and a variable number of edge servers. CVs are generally equipped with various kinds of sensors, and they are able to communicate with edge servers via low-latency networks, for instance 5G or LTE [42]. We assume that CVs leverage mobile edge computing capabilities (edge servers) to handle computationally intensive tasks, such as real-time data analysis, image classification, or route planning [43], in order to reduce delay processing and response latency and optimize some other significant parameters that are subject to constraints.

In particular, edge servers accept such requests to support CVs in satisfying task constraints. For instance, if a CV has to compute a route from a point to another point,

the benefit of contacting an edge server is represented by the wide availability of data, as well as the available computational power, which enables minimal processing delay. As a specific example, the navigation system must be responsive enough in order to give an indication within a certain threshold (e.g., 3 s).

The final result of the offloading task, in term of responsiveness, will give an indication of the "quality of service" in performing this task (e.g., processing delay, latency, and so on). Another aspect, in our view, is related to the "quality of the result". Indeed, for the same task, different results can be obtained on the basis of the available data: for instance, a given edge server may hold reliable and detailed data about real-time traffic, while some different edge servers may hold incomplete data that may lead to poor suggestions.

On the basis of these premises we introduce the collaboration model, with reference to the Figure 1. In the proposed scenario, the vehicles can actively collaborate by suggesting ways to offload tasks to edge servers. In some cases. a CV may receive the data of the request and organize the task offload on behalf of another CV (though this last modality is not always possible due to security and privacy concerns). More formally, this collaboration process is guided by two main metrics:

- Quality of Service: concerns the level of satisfaction of the main task requirements and/or constraints, which are mainly non-functional requirements, such as bandwidth minimization, processing time/delay, and so on;
- Quality of Result: evaluates how well a given CV can meet main functional requirements for a certain category of task through its own task offloading strategies, for example a task related to the navigation system of the vehicle.

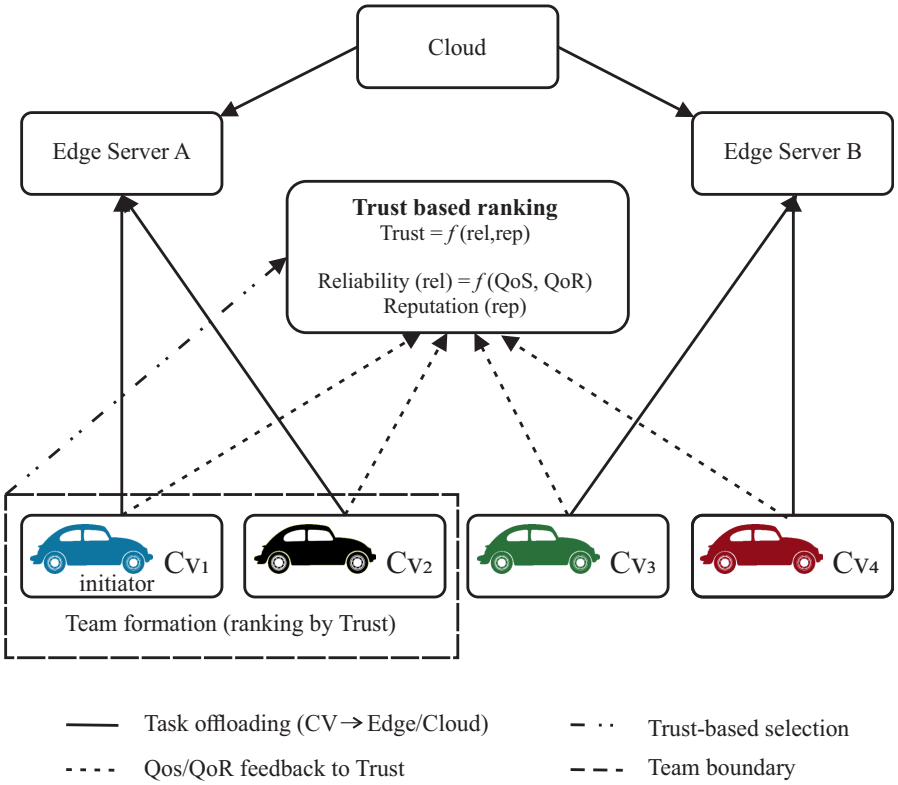


**Figure 1.** Connected vehicle and edge and cloud servers. Team formation.

Once a vehicle has joined a team, it will be trusted by the other members of the team and, as a consequence, it will be able to exchange information related to the effectiveness and the quality of results for a specific category of task. As we discuss in the next section,

this will imply the selection of the best suitable suggestion from a certain vehicle in order to offload a specific task.

## 4. The Trust Model

In this section, the proposed trust model, conceived to represent the performance of a CV providing for free some offloading tasks belonging to given categories $t$ within a MEC environment, will be described. In particular, the proposed trust model maps the qualitative measures previously introduced into quantitative measures and integrates them in a collaborative perspective characterized by mutual benevolence.

As stated in the previous section, any CV has the opportunity to exploit offloading tasks provided by other CVs and characterized from both a certain Quality of Service ($QoS$), which provides a measure about the satisfaction degree with respect to the main task requirements—i.e., latency or processing delay—and a certain Quality of Result ($QoR$), which refers to how much the result given by a computation is closed to the best possible result (for example, a route selected from a navigation system).

Now, let us introduce the following measures of performance for a generic CV $x$, which performs offloading tasks in a MEC. In detail, the CV reliability ($rel$) represents a synthetic measure regarding the capacity of the CV to reach a certain level of overall performance in performing offloading tasks for a given category $s$. In order to assign a value to the reliability measure, below we will assume that for the task category $s$, the two main components—i.e., Quality of Service and Quality of Result—can be both measured and combined in a linear way, as in the following Equation (1):

$$rel_x^s = \gamma_s \cdot QoS_x^s + (1 - \gamma_s) \cdot QoR_x^s \tag{1}$$

where the system parameter $\gamma_s$ is a real number ranging in $[0, 1]$ introduced to weight the relevance of $QoS$ with respect to $QoR$ in computing $rel_x$ on $s$ as perceived by a CV client $x$.

In our study, $\gamma_s$ was set empirically by testing different values in preliminary simulations and selecting the configuration that provided a balanced contribution of the two components. This allows the reliability metric to remain sensitive both to objective network performance (QoS) and to subjective outcome quality (QoR), without letting one dominate the other. Future work will explore adaptive mechanisms in which $\gamma_s$ is tuned dynamically according to network conditions or application requirements. We are assuming for the $QoS$—e.g., processing delay, latency and so on—that any software agent is able to assess a measure about the QoS provided from a service provider with respect to $s$, which is represented by a real number $QoS \in [0, 1] \subset \mathbb{R}$. Similarly, for the second parameter $QoR$, the quantitative evaluation can be given by any client of $x$—i.e., a user, or an AI agent capable of assessing the quality of the result of the offloading tasks—by means of a real number $QoR \in [0, 1] \subset \mathbb{R}$. Note that the measure $rel$ is stateless, and it is based on the fact that teams are temporary and characterized by a high variability in their compositions, which is an aspect tightly correlated with the nature of the urban mobility.

Secondly, let us to introduce the stateless reputation ($rep$) measure, computed as a real number belonging to $[0, 1]$ of a CV, which represents the capacity, as perceived by the members of a team $T$ about $x$, to reach a certain performance in term of reliability. More formally, at a given time within a team $T$ the reputation of $x$ is computed as in the following Equation (2):

$$rep_x^s = \frac{\sum_{m=1}^{N_T - 1} rel_{x,m}^s}{N_T - 1} \quad \forall \; CV \in T \neq x \tag{2}$$

where $N_T$ is represents the number of CVs in the team $T$.

Finally, we can compute the (stateless) CV trust measure, which represents the global *trust* measure of $x$'s performance to accomplishes with the tasks in the category $s$ within $T \in MEC$, as in the following Equation (3):

$$trust_x^s = \epsilon \cdot rel_x^s + (1 - \epsilon) \cdot rep_x^s \tag{3}$$

where we denote by $\epsilon \in [0, 1] \subset \mathbb{R}$ the system parameter weighting the relevance given to *rel* with respect to *rep*.

The *trust* measure defined in (3) integrates reputation and reliability by linearly combining them into a global measure for the given CV $x$. Such a trust measure is based on the reasonable assumption that, if an increment of reliability *drel* (resp., reputation *drep* yields an increment of trust *dtrust*, then the ratio $\frac{dtrust}{drel}$ (resp., $\frac{dtrust}{drep}$) should be identical for any increment of *drel* (resp., *drep*).

It should be noted that the adoption of a linear aggregation scheme was motivated by both interpretability and efficiency requirements. Linear combinations provide a transparent mapping between individual indicators (QoS, QoR, reputation) and the resulting trust value, which is desirable in safety-critical vehicular contexts where decision rationales must remain explainable. Moreover, the computational complexity of the linear model is constant per update, ensuring feasibility in highly dynamic scenarios. While more sophisticated nonlinear or machine learning-based approaches could potentially capture complex interdependencies among indicators, their integration is left as future work, as discussed in the concluding Section 6.

### *4.1. Computational Complexity*

The proposed trust model has been designed to remain lightweight and suitable for highly dynamic vehicular contexts. The computation of the reliability rel for a CV $x$ requires only the evaluation of two normalized indicators (QoS and QoR) and a weighted sum, which is a constant-time operation $O(1)$. Similarly, the update of the reputation rep corresponds to the average of the reliability values received from other team members. This operation is $O(z)$, where $z$ is the number of neighboring CVs participating in the team, and is therefore bounded by the team size. Finally, the computation of the trust value trust is again a simple linear combination of rel and rep, which is $O(1)$. Overall, the cost of updating the trust model per interaction remains very limited, ensuring scalability and real-time applicability in large-scale vehicular environments.

We will show via the experimental results described in Section 5 that this linear model is valid for our conceived scenario.

We highlight that both the values of the system parameters $\gamma$ and $\epsilon$ are reasonably chosen by considering the domain policies in terms of performance. In the experiments presented in Section 5, we set this value to 0.5 to assign equal relevance to the *QoR* with respect to *QoS* in the computation of the reliability measure and equal to 0.4 for the reputation with respect to the reliability in the computation of the trust measure, respectively. Moreover, consider that a newcomer CV will receive an initial trust value set to 0.5, which is an intermediate value that gives an opportunity to be chosen in some temporary team. Note also that in the presence of a stateless system such as the one proposed, this assumption will be valid only as long as the first service is provided by the newcomer CV.

### *4.2. Temporary Teams Formation Algorithm*

Given the ability of a CV to perform offloading tasks with a certain performance, the formation of temporary teams will be useful, at any CV, for asking to another CV to support a certain offloading task and/or to receive support on how an offloading task should be

executed. In this way, any CV in the team can exploit the benevolence, the ability, and/or the knowledge of the other CVs to perform offloading tasks for a certain category of tasks.

The main principle behind the design of our team formation algorithm is to allow CVs to properly select the most reliable partners for collaborative task execution. In this sense, our approach is built on the basis of the trust values which represent the combination of QoS, QoR, and reputation. In this manner, the CVs with stronger performance and reliability are more likely to be included in teams. The strengths of this approach are threefold: (i) it does not have the limitations of centralized coordination, as it is fully decentralized; (ii) it is capable of adapting dynamically to the different capabilities and behaviors of CVs. In particular, it ensures that teams remain effective also under highly dynamic mobility conditions; and (iii) it allows low-capability CVs to benefit from collaboration with more reliable partners, thus enhancing fairness. As a consequence, the overall robustness of the vehicular MEC system is improved.

Let $A$ be a generic team of CVs consisting of a CV $a_0$ that at a given time $t_0$ decided to start the team formation process by selecting eligible team members from a ranking based on their last trust scores. To this end, we assume that there exist at least $k$ connected vehicles in the communication range of the CV $a_0$ (for instance, CVs may use any communication module that supports the LoRa protocol [44]). Then, at the end of the formation process, we call $A = \{a_0, a_1, \ldots, \ldots a_n\}$, where $n \leq k+1$, the set of the connected vehicles built by the agent $a_0$ which, in turn, has executed the distributed team formation algorithm described below, and where $a_0$ represents the CV that has started the team formation process.

The team formation algorithm, depicted in Figure 2 is composed of five phases, namely starting, requesting, answering, selecting, and forming, as follows:

1. **Starting:** $a_0$ becomes aware of the necessity of forming a team to perform a task belonging to the category $s$. As stated before, we assume that the agent $a_0$ is aware that at least $k$ connected vehicles will be able to receive a broadcast message. Then, $a_0$ yields as inputs for this phase:
   - the maximum number of CVs ($mx$) in the temporary team, where $mx \leq k$;
   - the minimum number of CVs ($mn$) in the temporary team, where $mn \geq 1$;
   - a time threshold $T_h$, representing the time $a_0$ is available to wait for response from the potential team members;
   - the minimum value $trust_{min}$, required from $a_0$ to admit a CV to join with $A$.
2. **Requesting:** $a_0$ sends a broadcast message to the $k$ nearest CV to know (i) their availability, and (ii) their own experience (if any) with $j$, one of the other $k-1$ potential members of $A$. In other words, $a_0$ asks the values $rel^s_{j,m}$ for all $m \neq j$; these values will be used to compute the reputation values and, finally, trust values (see Formulas (2) and (3));
3. **Answering:** Each potential member of $A$ that received $a_0$'s request may be or not to be available to join with $A$. Therefore, each potential member either:
   - Does not send any response message. In this case, it is unavailable to join with $A$; or
   - Computes the values of $rel^s_j$ for all CVs different from $a_0$ and $a_j$. Then, these values will be sent back to the CV $a_0$.
4. **Selecting:** The following activities are executed:
   (i) Once the time threshold $T_h$ has elapsed, and assuming that the number of answers received from $a_0$ is $z \leq k$, then $a_0$ will calculate all the values $trust_j$ with $j = 1, \ldots, z$ in a list $L$; we remark that trust values $trust_j$ are calculated on the basis of the reliability values sent by the other potential members of $A$;

(ii) $a_0$ removes from $L$ those values $trust < trust_{min}$, since they are not eligible to be included in the temporary team $A$ (see below).

(iii) $a_0$ will order $L$ based on the increasing order of the trust score $trust$.

5. **Forming :** $a_0$ will extract $min(mx, length(L)) \geq mn$ CVs from $L$ with the higher values of trust. Then, $a_0$ sends a confirmation message to the CVs selected to join with $A$;

The team formation process is executed in a fully distributed manner, without the presence of any central registry or orchestration.

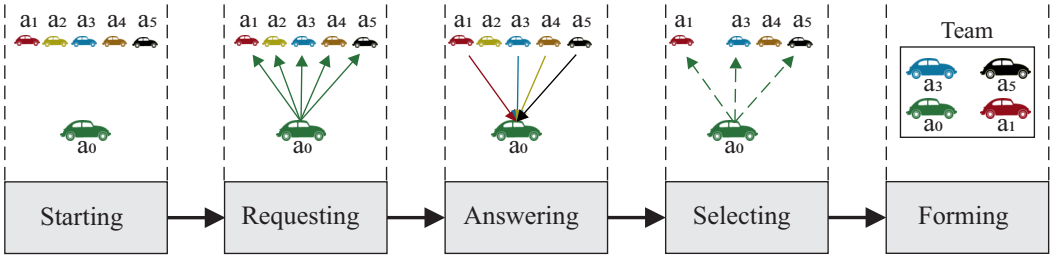


**Figure 2.** Temporary team formation.

*4.3. Computational Complexity*

The proposed team formation algorithm is also lightweight and scalable. In the requesting and answering phases, each vehicle exchanges at most one message with its $k$ neighboring CVs, which results in $O(k)$ communication overhead. In the selecting phase, the initiator $a_0$ computes the trust values of candidate members and orders them. This step requires $O(k)$ computations for trust evaluation and $O(k \log k)$ operations for sorting. Finally, the forming phase consists of sending confirmation messages to the selected members, which is $O(k)$ in the worst case. Therefore, the overall complexity of one team formation round is $O(k \log k)$, dominated by the sorting step [45]. This ensures that the algorithm remains efficient even when a relatively large number of vehicles are within communication range, making it suitable for highly dynamic vehicular environments.

## 5. Experiments

In this section, we describe the experiments we have performed to evaluate our approach. We have simulated the cooperation of the connected vehicles, implementing the algorithm described in the previous Section 4. In order to foster repeatability and to develop future researches, we implemented our simulations through a script in Octave language [46]. A significant number of tasks in five different categories were simulated (for our purposes, since the team formation is always related to a specific category of task, we analyzed the experimental results for a single category of task. Indeed, as expected, the results for every category of tasks were very similar).

As reported in Table 2 (lines 1–4), we 1000 simulated CVs over a simulation time of about 60 h, covering five task categories and a maximum of 50 CVs per group.

To ensure the reliability and replication of our evaluation, we provide further details about the simulation setup and parameter selection. The dataset consisted of synthetic mobility traces generated to represent a metropolitan traffic scenario with heterogeneous vehicle profiles, which allowed us to obtain variability in task demands and interaction opportunities. The choice of 1000 CVs and a simulation time of 60 h reflected a trade-off between scalability and computational feasibility, ensuring that the dynamics of temporary team formation can be observed over a sufficiently long horizon. The number of task categories (five) was selected to cover different offloading contexts (e.g., navigation, traffic management, and image classification), consistent with prior studies [47]. Parameters such as the initial reliability and reputation values (0.5) were set to neutral defaults, enabling

newcomers to fairly participate in interactions before building a history. The weights $\gamma$ and $\epsilon$ were set after preliminary tests to balance the relative influence of QoS versus QoR and reputation versus reliability; these values are in line with practices commonly adopted in trust modeling [12–14]. To model task requests, we adopted a Poisson distribution with $\lambda$ set to 20, a standard assumption for capturing the stochastic arrival of vehicular requests. QoS and QoR distributions were parameterized to create three distinct vehicle profiles ($p1$, $p2$, $p3$), representing high, medium, and low performers, thereby enabling us to evaluate the framework under heterogeneous conditions. Profile $p1$ corresponds to high-capability CVs, $p2$ to medium-capability CVs, and $p3$ to low-capability CVs with limited resources. This abstraction allows the trust model to reflect heterogeneity: vehicles with stronger MEC capabilities tend to achieve higher QoS and QoR scores, leading to higher trust values and more favorable selection in team formation. While this approach provides a manageable yet effective representation of heterogeneity, future extensions will refine the model by incorporating explicit parameters for processing power, memory availability, and energy constraints.

**Table 2.** Simulation parameters.

| No. | Parameter | Value/Range |
|---|---|---|
| 1 | Simulated time | 60 h |
| 2 | CVs | 1000 |
| 3 | No. of task category | 5 |
| 4 | Max no. of CVs per group | 50 |
| 5 | $Rel^{(0)}$ | 0.5 |
| 6 | $Rep^{(0)}$ | 0.5 |
| 7 | $\gamma$ | 0.5 |
| 8 | $\epsilon$ | 0.4 |
| 9 | CV requests per hours | Poisson distribution, $\lambda = 20$ |
| 10 | QoS | Normal Distribution |
| 11 | QoR | Normal Distribution |
| 12 | QoS $\{(\nu, \sigma^2)\}$ | $(\nu, \sigma^2) = \{p1 : (0.9, 1.0), p2 : (0.7, 1.0), p3 : (0.5, 2.0)\}$ |
| 13 | QoR $\{(\nu, \sigma^2)\}$ | $(\nu, \sigma^2) = \{p1 : (0.9, 1.0), p2 : (0.7, 1.0), p3 : (0.5, 2.0)\}$ |
| 14 | Ratio of $p1/p2/p3$ CVs in the simulated scenario | $\frac{1}{3}/\frac{1}{3}/\frac{1}{3}$ |

For the remaining parameters, we performed a few preliminary tests in order to set the framework parameters to suitable values, as reported in the remaining lines of Table 2. Parameters $\gamma$ and $\epsilon$ were set as indicated in lines 7 and 8 of Table 2. We set the initial value of *rel* and *rep* ($rel^{(0)}$ and $rep^{(0)}$) to the value 0.5 to give a "neutral" value of trust in a situation where did not yet possess reliability information, in view of subsequently updating the reliability on the basis of the next experience. The average number of requests per hour was set to follow a Poisson distribution (specified above in the detail), and the produced values of QoR and QoS to follow a normal distribution (lines 9–12 of Table 2). Parameters indicated at lines 12–13 of table 2 for $\nu$ and $\sigma^2$ were coupled to simulate three different CV profiles, $p1$, $p2$ and $p3$. Profile $p1$ was characterized by an average performance in QoR/QoS with a high variance $\sigma^2$, while the remaining profiles $p2$ and $p3$ were characterized by high performance and low variance.

In our simulations, the geographic positions of CVs were initialized by randomly distributing the vehicles over the considered area. During the simulation, mobility was modeled through synthetic random movements, where each CV updated its position according to a bounded speed range and randomized direction changes. This simplified

mobility formulation was chosen to maintain the focus on evaluating the trust and team formation mechanisms, without introducing variability due to specific road topologies or traffic traces. Future work will extend this model by integrating real vehicular mobility datasets and recognized simulators such as SUMO or Veins.

### *5.1. Results*

Figure 3 reports the evolution of the average trust values measured during the 60-hour simulation for the three profiles $p1$, $p2$, and $p3$. In addition to the average values, we computed the variance of trust values across simulation runs, which remained below 0.05 for $p1$ and $p2$, and around 0.08 for $p3$, indicating higher fluctuations for lower-performing vehicles. The shaded areas in the figure represent the 95% confidence intervals. These results confirm that the trust metric accurately follows the expected performance patterns: high-performing CVs ($p1$) exhibit stable trust, while less reliable CVs ($p3$) show wider oscillations due to their intrinsic variability.

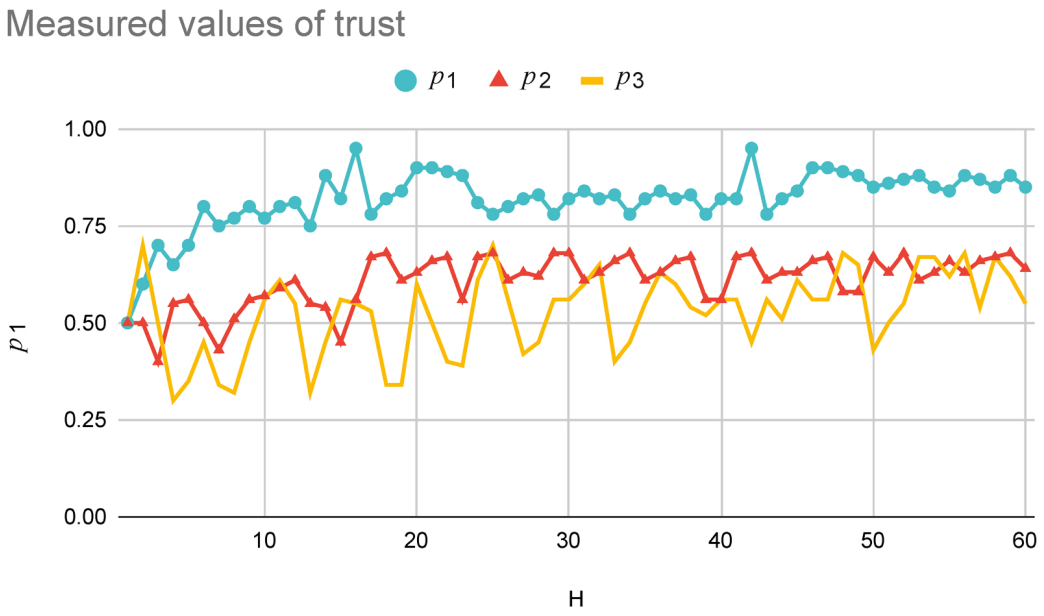


**Figure 3.** Measured trust values.

Since the main objective of group formation is represented by the possible advantage obtained by the generic CV, in term of performance, when contacting any other CV belonging to some of its own group, we measured the average performance reached by the CVs for their own task offloading (i.e., the QoS and the QoR) after a certain number of simulation hours. Indeed, in our approach, any CV can ask for the aid of another CV within its own group, or it can perform the task by itself. In particular, as explained in Section 4.2, once a CV has to perform a task offloading, it will contact another CV in one of its own teams if the trust of that CV is higher than its own reliability for the specific task category. After collecting these results, we repeated the same experiment by removing the team formation process. In this case, the behavior of the CV reflects one of two options: (i) to take the decision related to the task offloading on by itself, or (ii) to ask to any randomly selected CV in its own range for assistance. Then, we compared these measured values with those measured during execution of the team formation. For each of the three profiles, we computed the average value of *rel* obtained by the Formula (1) after X hours of simulation ($X = 10, 20, \ldots, 60$). We report the results in Figure 4. In particular, we marked as px-random and px-team the results obtained with the profile px and the random selection of a partner or the team formation based selection. Figure 4 compares the average reliability

obtained when CVs rely on team formation (*px-team*) versus random partner selection (*px-random*). For each profile, we ran 20 independent simulation trials and report mean values with 95% confidence intervals. The differences between *p*3-*team* and *p*3-*random* are statistically significant, confirming that low-performing vehicles benefit the most from trust-based team formation. For *p*2, the improvement is moderate but still consistent across trials, while for *p*1, the results of the two strategies are statistically indistinguishable, reflecting the fact that high-performing CVs are less dependent on collaborative mechanisms. These findings support the claim that the proposed trust model and team formation algorithm mainly enhance the performance of less capable vehicles, thereby improving fairness and overall system robustness.We observe that there is almost no difference between *p*1-team and *p*1-random. That is an expected result because the CVs profiled as *p*1 hold excellent performance in terms of obtained QoS/QoR in terms of task offloading (see Table 2). For the comparison *p*2-team vs *p*2-random we observe a slight improvement, as the CVs profiled as *p*2 exhibit good performance (see the simulated values of $\nu$ at lines 12 and 13 of Table 2), but when they belong in a team with CVs profiled as *p*1, they ask them for help, as the *p*1 CVs have higher values of trust with respect to the *p*2 CVs' own values. Finally, we observe, as expected, a significant increment in terms of performance in the CVs profiled as *p*3.

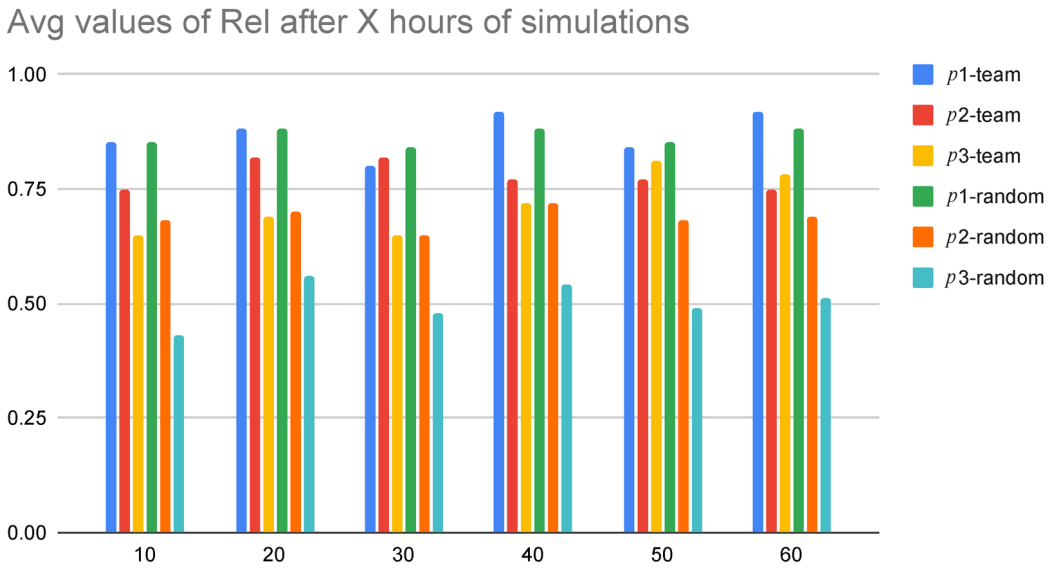


**Figure 4.** Team formation vs random selection of peers (CVs)—Average values.

### *5.2. Discussion*

While the first part of the experimental results was collected only to validate the numerical model built to measure the trustworthiness of the CVs, the second part (shown in Figure 4) allowed us to validate how much the team formation algorithm can provide an advantage to CVs that are not able to perform task offloading with high performance.

In particular, the results obtained about profile *p*3 represents the most significant results shown in Figure 4. Indeed, we remark that profile *p*3 was specially arranged as having low average values of QoS/QoR and high variance. From Figure 4 it becomes clear that, after a few hours of simulations, the average performance of such CVs labeled *p*3 get values higher than 0.5. Moreover, in the second part of the simulation, the computed values of rel increase and seem to become stable around the value of 0.7.

## 6. Conclusions

In this paper, we introduced a collaborative framework for supporting task offloading in connected vehicular environments through the dynamic formation of temporary teams

of CVs in a MEC scenario. The proposed approach combines three key elements: (i) a novel trust model integrating both Quality of Service (QoS) and Quality of Results (QoR) into a unified reliability score; (ii) the combination of this reliability measure with distributed reputation sharing to compute trust; and (iii) the exploitation of the resulting trust metric to guide a decentralized team formation algorithm. The simulation results demonstrated that our approach improves task execution quality and responsiveness, particularly for low-performing vehicles, thereby contributing to more efficient and fair collaboration in vehicular networks. Beyond these scientific contributions, our framework has practical implications for real-world vehicular edge systems. By relying on lightweight computations and decentralized decision-making, it can be deployed in dynamic urban traffic scenarios without requiring centralized coordination. This makes it potentially suitable for integration with edge infrastructures deployed in modern smart cities, supporting applications such as cooperative navigation, traffic management, and safety-critical services.

It is worth noting that the experimental validation presented in this work was conducted through controlled simulations, with the aim of isolating the contribution of the proposed trust and team formation model. While this setup allows a clear evaluation of the framework in a reproducible manner, future work will focus on extending the experiments by using real vehicular mobility datasets and established simulation platforms such as CARLA [48], SUMO [49] or Veins [50]. This will enable us to assess the scalability, robustness, and practical applicability of the framework in more realistic and heterogeneous traffic scenarios.

The discussed findings validate the core hypothesis that supporting vehicular networks with a trust model and a decentralized team formation algorithm can substantially enhance MEC-assisted computation. Nevertheless, in the future, we will focus on extending the trust model to include additional contextual parameters such as mobility patterns, energy availability, and dynamic task priorities. This would allow us to perform comparisons with different approaches. Furthermore, we aim to evaluate the scalability of the system in real-world vehicular network simulators and explore the integration of security mechanisms to protect the trust framework against malicious behavior or manipulation. In addition, the current trust model relies on linear aggregation of QoS, QoR, and reputation values. This choice was guided by the need for interpretability and computational efficiency in highly dynamic vehicular scenarios. Nevertheless, an interesting avenue for future research is the adoption of nonlinear or machine learning-based techniques (e.g., regression models, neural networks, or reinforcement learning) to capture more complex dependencies among indicators and potentially enhance prediction accuracy. We plan to explore these extensions in future work to further strengthen the adaptability of the proposed framework.

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