Scaling A Blockchain System For 5G-based Vehicular Networks Using Heuristic Sharding

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***Abstract*—5G communications are expected to expand both capacity and flexibility in future vehicular networks. However, due to the wide coverage range of 5G-based networks, massive device access in the 5G era will pose great challenges in access control and terminal management. In order to address the scalability issue in large-scale 5G-based vehicular networks, we propose in this paper the use of two heuristic sharding schemes which are based on the *Determinantal Point Process* (DPP) with different complexities. Specifically, in the proposed algorithms, both location and wireless channel condition of a base station (BS) are jointly considered respectively as diversity and quality parameters in the DPP. Both of them can effectively control the size of each shard, ensure the shards are evenly distributed and allow in-shard cooperation among the BSs. The communication robustness is then greatly improved due to the efficient in-shard cooperation and the system guarantees stable throughput even in scenarios where transactions volume changes dynamically. While compared to benchmark schemes, the simulation results of the proposed protocol and algorithms show significant performance gains in terms of coverage and load balancing.**

***Index Terms*—5G-based vehicular networks, blockchain, sharding, scalability.**

I. Introduction

In the past few years, with the development of navigation safety requirements as well as the investments of car manufacturers and Public Transport Authorities, significant research efforts have been witnessed on the subject of vehicular networks. Vehicular networks have been considered as an important use case in the future 5G wireless system since they have significant potential to enable diverse applications associated with traffic safety and efficiency. With the development of communication technology, 5G communications will expand the capacity and flexibility of the existing vehicular networks, and extend upon what services they can deliver [1]. Over time, vehicles will be given the potential to communicate with each other in entirely flexible, reliable and secure ways.

In 5G-based vehicular networks, the reliability of information is extremely important since rich applications are expected to be supported and many of them are directly related to the driving safety [2]. Misleading information from unreliable sources can seriously affect the effectiveness of services and can further lead to the death of people. However, as we know, most on-broad units (OBUs) are card-free devices, existing standards also do not make clear specifications for their functions and identity information, which makes it difficult to establish an effective unified device management system like public key infrastructure (PKI) to ensure the integrity and reliability of information sent by users. For these reasons, it is desired to fully take advantages of 5G networks, in terms of high-throughput and low-latency, to establish an effective distributed access control and information reliability management system.

In order to address the trust issue in 5G internet of things (IoTs), distributed identity (DID) [3], [4] is proposed on top of distributed ledgers or blockchain systems, which leverages a global key-value database to enable secure management and storage of digital identities for users. For example, Microsoft proposed recently Identity Overlay Network (ION) [5], where the users' DIDs are calculated based on their public keys stored in the Bitcoin ledger, which can address the above trust concerns in a decentralized and potentially hostile environment by enabling registering and updating transactions securely in a decentralized fashion via consensus among participants. However, one major issue that needs to be addressed in large-scale blockchain systems is scalability, especially in ultra-dense deployed vehicular networks. Non-scalable blockchain systems may face issues such as high transmission delay or high consensus failure rate, especially in highly dynamic vehicular networks.

Recently, sharding has been considered as a major approach to overcome the scalability problem of blockchain protocols. Several works proposed using sharding algorithms to establish high-throughput and low-latency blockchain systems since splitting the system into several independent shards can greatly reduce the broadcast load in decentralized blockchain systems [6]. For their proposed sharding methods, in [7] nodes are assigned to committees in an unbiased and random manner. In [8], the nodes belonging to the same sharding committee discover each other via a peer-discovery algorithm. And in [9] [10], the authors proposed to assign nodes into committees based on their established identities. Unfortunately, none of these methods can be used in the vehicular networking environments, since 1) nodes assigned to the same shards according to a random sampling can be located far from each other, which reduces the system throughput and may cause interference to the nearby nodes belong to other shards; 2)

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several important norms like channel conditions and interference between nodes are not considered in these methods, which may lead to differences in throughput between different shards and affect the reliability of consensus. Moreover, due to the open nature of wireless channels, resource allocation is another important norm that needs to be considered in sharding. Especially in ultra-dense deployed systems, which usually makes the problem NP-hard. Therefore, address the scalability issue via sharding in 5G vehicular networks remains challenging.

In this paper, in order to address the scalability issue in large-scale 5G-based vehicular networks, we propose two heuristic sharding algorithms based on Determinantal Point Process (DPP) with different complexities. Specifically, in the proposed algorithms, both location and wireless channel condition of a base stations (BS) are jointly considered as respectively diversity and quality parameters in the DPP. Both of them can effectively control the size of each shard, ensure the shards are evenly distributed, and allow in-shard cooperation among the BSs. The communication robustness is then greatly improved due to the efficient in-shard cooperation and the system guarantees stable throughput even in scenarios where transactions volume changes dynamically. The effectiveness of the proposed algorithms is studied under different network conditions via simulations.

II. A Blockchain System For 5G-based Vehicular Networks

A. Network Model

A 5G-based vehicular network consists of a set of base stations (BSs) and road side units (RSUs) deployed at the road sides communicating with the vehicles moving along the road. In this paper, we consider a scenario consisting of several macro cells, which is given in Fig. 1. Each macro cell is covered by a BS, who collects transactions within its cover range and participates in consensus. BSs are connected to the gateway via S_1 link and each two adjacent BSs are connected by X_2 links. In each macro cell, several single-antenna RSUs are located, connected to the BSs via wireless links. Each roadside unit can communicate with multiple base stations simultaneously.

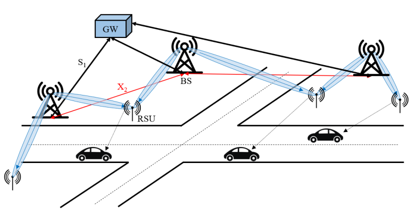


Fig. 1: Infrastructure of 5G vehicular networks.

B. Consensus Protocol

As a kind of peer-to-peer overlay system, the blockchain system needs to choose consensus protocols that compatible with its physical underlay network to maximize its efficiency. Especially in 5G Era, wireless transmission rate is significantly increased [11], inefficient consensus protocols will become the bottleneck of the blockchain system. Since vehicular networks are permissionless, the network infrastructures such as BSs and RSUs are all pre-established and reliable, in this paper, we assume that a synchronous BFT-class Consensus protocol is used in our considered 5G vehicular blockchain system, wherein the BSs participates in the consensus as committee nodes. BFT-class consensus protocol is a more suitable choice compared to the bitcoin system since they can avoid large-scale and meaningless PoW operations and have high fault tolerance.

The first widely used BFT-class consensus protocol Practical Byzantine Fault Tolerance (PBFT) protocol [12] was proposed in 2002, which is designed based on the Byzantine Fault Tolerance and can reduce the message complexity level from the exponential level to a polynomial level. However, PBFT protocol is difficult to support ultra-dense deployment network environments due to the FLP possibility [13] of asynchronous consensus and more importantly, there is a lack of reliable broadcast protocols in the p2p overlay networks. In order to address this issue, many modifications are proposed recently to improve the Byzantine fault tolerance, transaction throughput, consensus robustness and synchronous of the PBFT protocol [14] [15].

In 5G networks, since reliable X_2 and S_1 links are used between BSs and between BSs and the gateways. Based on the aforementioned work on BPFT protocol optimization, the implemented consensus protocol in this work should meet the following requirements, which can significantly reduce the consensus overheads:

- Parallel block generation: In 5G networks, BSs are connected via high-speed wired links, transactions can be shared among BSs through high-reliability broadcasts. We propose to select BSs as committee members to achieve low latency parallel block generation.
- Scalable committee: In 5G vehicular networks, BSs and RSUs are ultra-intensive deployed. We propose to use sharding strategy to control the number of committee nodes to reduce the complexity of consensus and take full advantage of the intra-shard cooperation to improve the throughput and reliability of transaction sharing.
- One-round commit: Due to the reliable broadcasting and parallel block generation, committee nodes only need to make a one-round commit on the hash of the newly generated block to finish the consensus, which can greatly reduce the complexity and latency of the consensus.

III. Determinantal Point Processes (DPPs) Bsaed Sharding Algorithms

As discussed in the previous sections, sharding is a desired method to address the scalability issue in large scale blockchain systems. For example, assign n nodes into m shards ($m << n$) and each shard corresponds to a committee node, can significantly reduce the consensus complexity. However, ultra-dense deployment and the open nature of wireless channels make 5G vehicular network a more complex system and a lot more norms are needed to be jointly considered and balanced during the sharding procedure to ensure the reliability and effectiveness of the consensus. At least, the following three conditions should satisfied: 1) the shards should be evenly distributed in the area and the size of each shard should be at the same size; 2) the impact of inter-shard interference should be significantly reduced; and 3) the in-shard cooperation is desired to reduce the communication delay.

To the best of our knowledge, there is no proposed shading method can satisfy all these conditions simultaneously. To this end, we propose in this paper two DPPs based heuristice sharding algorithms to address these issues since with DPPs, both quality norm and diversity norm are jointly considered, which makes the sharding results more balanced.

A. Determinantal Point Processes (DPPs)

Generally speaking, DPPs [16] are strong probabilistic models to reflect the diversity among samples, which can be used to balance "quality" and "diversity" in subset selections. A DPP is a distribution over subsets of a fixed ground set.

We consider a blockchain system consist of m BSs and divide it into n shards. For two BSs i and j in our considered network, vector $\mathbf{f}_i$ denotes the location of BS i which is used as a diversity measure. Thus, a Gaussain kernel $S_{ij} = e^{-\frac{||\mathbf{f}_i - \mathbf{f}_j||^2}{\sigma^2}}$ can be defined to describe the location variance between them. And q_i is the quality measure which can be considered as the transaction volume received at BS i or the channel quality within this area.

In this way, in order to jointly measure the quality of each BS and the diversity among them, a $m \times m$ real and symmetric matrix L can be defined, wherein each element L_{ij} can be given by:

$$L_{ij} = q_i S_{ij} q_j \quad \forall i, j \leq m. \tag{1}$$

Then, the log transform of the probability that BS i and j are selected as committee member can be given by:

$$\log\det(L_{\{i,j\}}) = \sum_{u \in \{i,j\}} \log(q_u^2) + \log \begin{vmatrix} S_{ii} & S_{ij} \\ S_{ji} & S_{jj} \end{vmatrix}, \tag{2}$$

where $\log \begin{vmatrix} S_{ii} & S_{ij} \\ S_{ji} & S_{jj} \end{vmatrix} = \log(1 - S_{ij}^2)$. It can be observed that when the selected BS i is close to the BS j, the value of $\log(1 - S_{ij}^2)$ is small. That is, the probability that both BSs i and j are selected as committee member is small. In the following, we will propose two different sharding algorithms.

B. DPP-Maximum Likelihood Estimation (MLE) Algorithm

L-ensembles are a slightly restricted but a useful class of DPPs. With L-ensembles, a real and symmetric matrix L indexed by the elements of $\mathcal{Y}$ is defined and the probability of sampling a set of $X \subset \mathcal{Y}$ can be given by

$$P(X) \propto \det(L_X). \tag{3}$$

And we have

$$P(X) = \frac{\det(L_X)}{\det(L+I)} \tag{4}$$

since $\sum_{X \subseteq \mathcal{Y}} \det(L_X) = \det(L+I)$, where I is a diagonal matrix.

In this algorithm, the channel quality and the average transaction volume received at each BS are jointly considered. Thus, the quality measure for the i-th BS q_i can be given by

$$q_i(\theta_1, \theta_2) = e^{\frac{\theta_1 D_i + \theta_2 \zeta_i}{2}}, \tag{5}$$

where D_i denote the transactions received by the BS i and ζ_i represents the average channel quality within the cover range of BS i.In this way, the probability that the subset X is selected can be given by

$$\begin{aligned} P_{\vec{\theta}}(X) &= \frac{\det(L_X)}{\det(L+I)} \\ &= \frac{\prod_{i \in X} e^{\theta_1 D_i + \theta_2 \zeta_i} \det(S_X)}{\sum_{X' \subseteq \mathcal{Y}} \prod_{i \in X'} e^{\theta_1 D_i + \theta_2 \zeta_i} \det(S_{X'})}. \end{aligned} \tag{6}$$

There are several objective function that can be used for learning and we focus on maximum likelihood (ML) learning. The objective of ML learning is to choose the optimal vector $\vec{\theta^*} = (\theta_1^*, \theta_2^*)$ to maximize the following log-likelihood function

$$\begin{aligned} L(\vec{\theta}) &= \log \prod_{t=1}^{T} P_{\vec{\theta}}(X^{(t)}) \\ &= \sum_{t=1}^{T} (\theta_1 \sum_{i \in X^{(t)}} D_i + \theta_2 \sum_{i \in X^{(t)}} \zeta_i + \log\det(S_{X^{(t)}}) \\ &\qquad - \log \sum_{X' \subseteq Y} \prod_{i \in X'} e^{\theta_1 D_i + \theta_2 \zeta_i} \det(S_{X'})). \end{aligned} \tag{7}$$

Thus, the problem can be given by

$$\vec{\theta}^* = \arg max \ L(\vec{\theta}). \tag{8}$$

Since the log-likelihood function $L(\vec{\theta})$ is concave to $\vec{\theta}$ [17], the maximum value of $L(\vec{\theta})$ can be obtained using gradient ascent method. Its gradient $\nabla L(\theta)$ can be given by

$$\nabla L(\vec{\theta}) = \sum_{t=1}^{T} (\sum_{i \in X^{(t)}} (D_i, \zeta_i) - \sum_i K_{ii}(D_i, \zeta_i)), \tag{9}$$

where K_{ii} is the i-th element on the diagonal of the marginal kernel matrix K. Since the matrix L can be eigendecomposed as

$$L = \sum_{n=1}^{N} \lambda_n \nu_n \nu_n^T. \tag{10}$$

Thus, K_{ii} can be calculated as follow

$$K_{ii} = \sum_{n=1}^{N} \frac{\lambda_n}{\lambda_n + 1} \nu_{ni}^2. \tag{11}$$

At last, we discuss the selection of subset X since it will directly affects the learning quality of the DPP-MLE algorithm. In order to find the most suitable subset, we firstly fix the number of shards and then solve the following optimisation problem to finish the sharding procedure

$$\max \quad \min_{j} \quad \frac{\operatorname{diag}(\mathbf{S}_j \mathbf{W}_j)}{\sum_i W_{ij}} \tag{12}$$

$$s.t. \quad \max(\mathbf{W}_j \mathbf{D}_j^T) \leq \frac{1}{k} \sum_j (\mathbf{W}_j \mathbf{D}_j^T), \quad \forall j \tag{12a}$$

$$\sum_j (W_{ij}) = 1, \qquad \forall i \leq m \tag{12b}$$

$$W_{ij} \in \{0, 1\}, \qquad \forall i, j, \tag{12c}$$

where vector $\mathbf{W}_j = \{W_{1j}, \dots W_{mj}\} \in \mathbb{Z}^{1 \times m}$ denotes the BSs in shard j and vector $\mathbf{S}_j = \{\zeta_{1j}, \dots \zeta_{mj}\} \in \mathbb{R}^{m \times 1}$ represents the channel quality in shard j. In this optimization problem, we try to maximize the average channel quality in the worst-case shard. Constraint $(12a)$ gives the upper bound of transaction amount in each shard, wherein the variable k can be set based on the number of shards. Constraint $(12b)$ specifies that each BS can only be in one shard. Problem (12) is an integer linear programming problem, which can be effectively addressed by using Lingo. Then we select one BS each shard as committee nodes based on the channel quality and add them into the set X, for next step training algorithm.

In this way, as given in Algorithm 1, we propose a ML learning algorithm to train vector $\vec{\theta}^*$. In this algorithm, we select a subset X of size n by solving the optimisation problem (12), which can guarantee the optimality of $\vec{\theta}^*$ obtained.

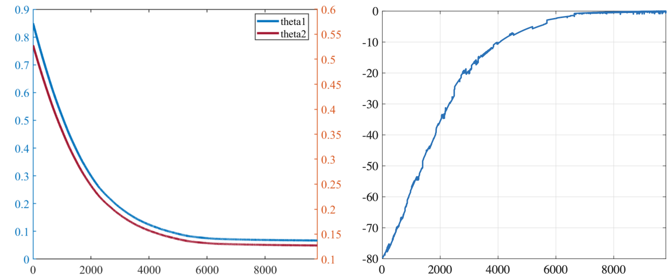
Algorithm 1 DPP-MLE Algorithm

Input: instance X,initial parameters $\vec{\theta}$,strive α,stopping criteria ϵ
Output: trained parameters $\vec{\theta}$

```
do
    ∇L(θ) ← 0
    for (X_i, Y_i) ∈ (X, Y) do
        Compute kernel L_i with parameters θ
        Eigendecompose L_i = Σ_{i=1}^m λ_i ν_i ν_i^T
        for j ≤ m do
            K_jj ← Σ_{i=1}^m (λ_i/(λ_i+1)) ν_ij^2
        end for
        ∇L(θ) ← ∇L(θ) + Σ_{j∈X_i} f_j − Σ_j K_jj f_j
    end for
    θ ← θ + α∇L(θ)
while norm(∇L(θ)) > ε
return θ*
```

C. DPP-Maximum a Posteriori Inference (MAP) Algorithm

In this part, we propose a low complexity DPP-MAP based sharding algorithm, wherein only the location of BSs and the average transaction volume received at each BS are considered to ensure that the selected committee set is evenly distributed within the area and the transaction volume to be processed in each shard is relatively balanced. In this case, the quality measure $q_i = D_i$.



(a) Convergence of $\vec{\theta}$ (b) Convergence of gradient

Fig. 2: Convergence of $\vec{\theta}$ and gradient of DPP-MLE likelihood function.

As given in Algorithm 2, we propose a greedy MAP algorithm to select the committee set X ($|X| = n_s$). We firstly add the BS who has received the biggest volume of transaction into set. And in the following iterations, add one BS each round into set until the number of committee nodes meets the requirements. In each iteration, BS j will be selected if it satisfies:

$$j = \arg\max_{i \in \mathbb{Z} \setminus X} \log\det(L_{X \cup \{i\}}) - \log\det(L_X), \tag{13}$$

where $\mathbb{Z}$ is the set made up of all BSs.

Algorithm 2 Greedy DPP-MAP Algorithm

Input: Kernel L,target number of committee nodes n_s, Set $\mathbb{Z}$
Output: Set X

```
while |X| < n_s do
    if |X|==0 then
        i ← arg max log(diag(L))
        X ← i
    end if
    j = arg max_{i∈Z\X} log det(L_{X∪{i}}) − log det(L_X)
    X ← X ∪ {j}
end while
return X
```

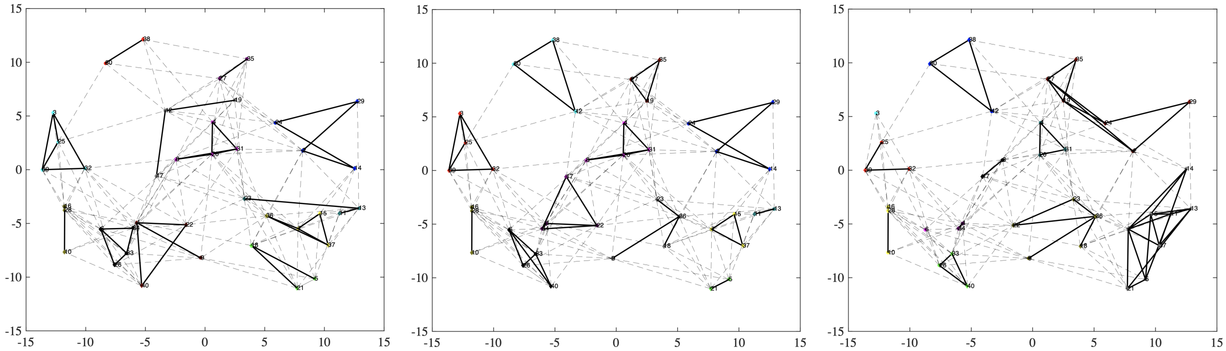
After the selection of committee set, each committee node can define a shard. Thus, set C_i can be recognized as a shard contains committee node i. Afterwards, considering the efficiency of in-shard cooperation, the rest BSs will be classified into the nearest shard. For example, BS k can be classified into shard C_i if the following condition stands:

$$\frac{\sum_{l \in C_i} d_{lk}}{|C_i|} \leq \frac{\sum_{l' \in C_j} d_{l'k}}{|C_j|}, \quad \forall j \in X \setminus \{i\}, \tag{14}$$

where d_{ik} is the Euclidean distance between two BSs l and k.

IV. Simulation Results

In this section, we provide simulation results to evaluate the performance of the proposed consensus protocol with sharding. In the simulations, we consider a 30×30 square region, wherein 40 BSs and 120 RSUs are located randomly. The X_2 link is established between adjacent base stations if the distance between them does not exceed a fixed threshold



(a) DPP-MLE algorithm (b) DPP-MAP algorithm (c) KMM algorithm

Fig. 3: Sharding results for 3 different algorithms (40 BSs into 12 shards).

r. Each base station is connected to the gateway via S_1 link. In each round, the total volume of transactions generated in the entire area is fixed, but the transaction volume received by each base station is randomly generated. The parameter settings in the simulation are summarized in Table I:

TABLE I: PARAMETERS USED IN SIMULATION

Parameter	Value
Simulation Environment	Urban
Path Loss Exponent	2
Number of BSs	40
Number of RSUs	120
Fading model	Rayleigh
Transit power (BSs, RSUs)	100mw and 50mw
Noise power	-95 dBm

In order to fairly evaluate the performance of our proposed methods, since the sharding algorithms discussed in Section I are not applicable in 5G vehicular networks, we choose kMM [18], one of the simplest and popular unsupervised machine learning algorithm as a benchmark scheme, wherein both the location of BSs and channels qualities are considered. specifically, we randomly select n BSs as cluster heads then iteratively update the mean distance in each cluster to optimize the positions of the cluster heads until converge. In order to achieve fast convergence, only the locations of the BSs are considered during the clustering process.

First, we discuss the choice of training set, in order to make the training set and the test set the same distribution, we set a 15×15 square region, wherein 10 BSs and 30 RSUs are located randomly. By solving the optimization problem (12), the optimal subset X can be obtained. Then, by setting the initial $\vec{\theta} = (0.8493, 0.5280)$ and the stopping criteria $\epsilon = 10^{-4}$, the convergence behaviour of our proposed DPP-MLE algorithm is illustrated in Fig. 2. Since we set the stopping criteria to 10^{-4}, the entire convergence process went through 10^4 iterations. If we set the stopping criteria to 10^{-3}, it only takes less than 1000 iterations to complete the convergence. The obtained $\vec{\theta}^* = (0.0672, 0.1274)$, which can be used for sharding in next step.

In Fig. 3, the sharding results for all three algorithms are illustrated. The dashed lines represent the X_2 links between the BSs and the bold lines show the shards. In this case, we consider to divide 40 BSs into 12 shards, where we use different colours to indicate different shards. It can be observed that compared with the KMM sharding algorithm, the shards obtained by our proposed DPP-MLE and DPP-MAP algorithms are more evenly distributed. In 3 (a) and 3 (b), only near the edge there are several shards contain only two BSs, but in 3 (c), two shards contain only one BS. Under the assumption that the RSUs can be communicate to different BSs, the cooperation between BSs can clearly improve the stability of communication and reduce the communication delay. Especially in the synchronous consensus protocol, the consensus delay often depends on the communication delay in the worst-case shard.

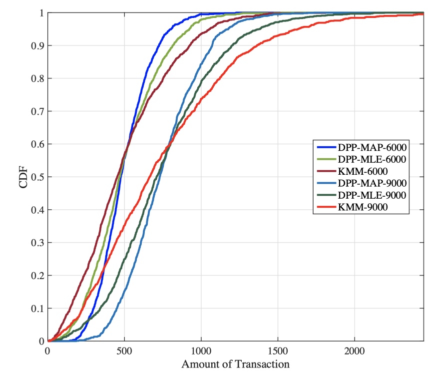


Fig. 4: CDF of the amount of transaction in each shard.

The cumulative distribution function (CDF) of the amount of transaction in each shard is given in Fig. 4. We chose two scenarios with a total transaction volume of 6000 and 9000 in the region, and launched 100 simulations for each algorithm in each scenario in order to evaluate the performance of our proposed scheme in different channel conditions. It can be observed that, in both scenarios, our proposed DPP-MLE and DPP-MAP algorithms have better performance than the KMM algorithm. It is mainly manifested in the curves whose rate of change is higher than that of the KMM algorithm, indicating that the transaction distribution in each shard is relatively even, which can effectively reduce the transmission delay in shards with poor channel quality, thereby reducing the delay of the consensus protocol. At the same time, it can also be observed that in both scenarios, the performance of our low-complexity DPP-MAP algorithm is slightly lower than that of the DPP-MLE algorithm.

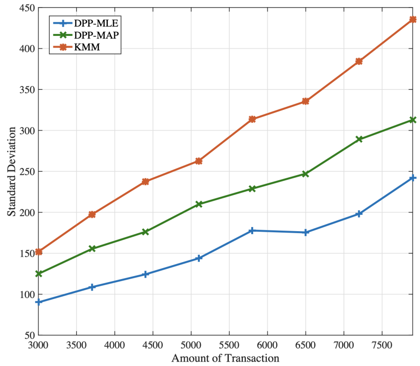


Fig. 5: Average standard deviation of the transaction volume in each shard based on 100 simulations.

In order to further test the performance of our proposed sharding algorithms in terms of load balancing, we selected 8 different points between the total transaction volume of 3000-8000 for simulation. In the simulation process, 100 simulations were performed for each algorithm in each scenario, and this time we focus on the standard deviation of the transaction volume in each shard and calculated its average based on the results of 100 simulations. As given in Fig. 5, it can be observed that as the total transaction volume increases, the standard deviation of transaction volumes in different shards is also increasing. This shows that the larger the total transaction volume, the more difficult to balance the load through sharding methods. However, the performance of our proposed DPP-MLE and DPP-MAP algorithms are all far better than the KMM algorithm, and a larger performance gap can be observed between the DPP algorithms and the KMM algorithm with the increase of transactions.

V. Conclusion

In the last few years, the DID has been considered as a promising technique to address the trust issue in 5G vehicular networks, leveraging a global key-value database that enables a secure management and storage of digital identities for users. However, the scalability remains a major issue in large-scale and ultra-dense deployment systems, especially in wireless environments, which always make the sharding problem NP-hard. In this paper, and in order to address the scalability issue in large-scale 5G vehicular networks, we proposed two heuristic sharding algorithms based on Determinantal Point Process (DPP) with different complexities, which can effectively control the shards size and allow in-shard cooperation among base stations (BSs). Using the proposed algorithms, the communication robustness has been greatly improved through the efficient in-shard cooperation and the overall system guarantees stable throughput even in scenarios where transaction volumes change dynamically. The simulation results show that our proposed algorithms converge quickly and significant performance gains in terms of load balancing in comparison to benchmark schemes.As a future work, a focus will be on solving the problems for practical implementation and analyse the in-shard cooperation among BSs, especially for the inter- and intra-shard interference cancellation problem.

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