Blockchain based Model for Nondeterministic Crowdsensing Strategy with Vehicular Team-Cooperation

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***Abstract*—Smart vehicles can cooperate in teams to perform crowdsensing tasks in smart cities. A critical challenge in this regard is to build a secure model for nondeterministic vehicle teams to achieve maximum social welfare. Although several crowdsensing models have been proposed, none of them has focused on real-time vehicle teamwork. In this study, to the best of our knowledge, we propose the first secure model, called Blockchain-based Nondeterministic Teamwork Cooperation(BNTC), for nondeterministic teamwork cooperation in a vehicular crowdsensing system. We model the system as a multi-conditional NP-complete problem by explicitly considering the dynamic features of task issuers and workers. To solve the problem, we propose Winning Teams Selected(WTS) algorithm based on a reverse auction and utilize a knapsack-based method to solve the models. We consider credit of teams for determining the payment. Thus, we propose a Credit-based Team Payment(CTP) algorithm for BNTC to maximize the welfare of the system. We also propose a general blockchain-based framework to address trust issues and security challenges to make the method suitable for use in practical applications. Based on theoretical analyses and extensive simulations, we demonstrate that the proposed model performs better than the baselines and can achieve the maximum social welfare. Implementation with Ethereum suggests our model can operate within a reasonable cost.**

***Index Terms*—Smart Cities, Blockchain, Mobile Crowdsensing, Team Perception**

I. Introduction

WITH the development of the Internet of Things, smart vehicles are now equipped with many components to provide a better driving experience, such as wireless network interfaces [1], environmental sensors, vehicle computers, and smart user interfaces[2]. Many smart vehicles and Road Side Units (RSUs) can support for mobile crowdsensing(MCS)[3]. A MCS platform issues tasks such as pollution detection[4], mobile advertising[5] and task computing[6] to the vehicles (i.e., workers) that participate in the system according to their willingness and bidding price. However, in practice, users are not willing to participate in vehicular crowdsensing applications owing to the lack of an appropriate incentive strategy and concerns about the leakage of private information when sharing data. Thus, an effective incentive strategy and safe platform are important for MCS.

Typical crowdsensing schemes function well for tasks that require a single worker; however, tasks that require real-time cooperative teamwork by multiple workers are likely to fail because of subtask failures by some workers or time-outs due to a lack of sufficient workers. In addition, multiple vehicles can form a pool of powerful computing resources because of the increasing computing capacity of vehicle computers. The computing power of the massive number of vehicles on roads can significantly support computational tasks in smart cities due to the development of distributed computing. However, efficiently utilizing the computational power of numerous vehicles on the roads in a smart city remains to be an unresolved problem. Thus, building a secure MCS mechanism for IoV with suitable incentives based on teamwork is an important issue for smart cities. What's more, for determination of payment for workers, some works pay a worker according to highest utility value based on external pricing [7], without considering credit and fairness of overall utility, which are meaningful evaluation metrics to indicate the performance of the worker and MCS system.

In the present study, to address the problems described above, we design a model called Blockchain-based Nondeterministic Teamwork Cooperation(BNTC) in a MCS system with IoV to exploit the real-time collaborative computing power of numerous vehicles to complete MCS tasks which require teamwork. The main contributions of the present study are as follows.

1) We design a novel model based on nondeterministic crowdsensing for vehicular teams. A real-time MCS task can be distributed by the MCS platform to one or more vehicular teams directly rather than to some single vehicles. Vehicles equipped with smart devices form teams to complete tasks. The model based on teamwork can improve the completion ratio for tasks by selecting appropriate teams according to their capabilities.

2) To determine the distribution of tasks, we propose an optimized reverse auction mechanism based on the knapsack algorithm called WTS algorithm for BNTC, where it considers

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task completion ratio, social cost, and number of teams selected. We consider the impact of credit factors on the critical payment and propose a CTP method for BNTC, which is inspired by the payment determination algorithm described by [7]. The two algorithms can ensure that the model maximizes the social welfare.

3) We propose a blockchain-based framework for the non-deterministic MCS with IoV model. All members in the system are in a blockchain. Key services are handled by smart contracts. The framework can ensure the privacy of data for users and the data integrity for the system. The workers can work and receive payments anonymously. The fairness of the payments is guaranteed and the framework makes the model suitable for practical applications.

II. RELATE WORK

A. Incentive Mechanisms for Mobile Crowdsensing

Incentive mechanisms are employed to select appropriate workers and to determine suitable payments for workers in different application models, and to ensure that the social welfare is maximized [8][9][10]. Wang et al. [11] proposed a graph-based solution to transform Minimum-Delay-Maximum-Coverage and Minimum-Overhead-Maximum-Coverage to a connection routing search problem. And Greedy-based recursive optimization approaches were proposed to address the two problems with a divide-and-conquer mode. Gao et al. [12] considered different vehicle trajectories and the uncertainty of driving routes to establish a MCS task system where each task could be performed jointly by multiple vehicles. Chen, et al. [13] studied location-ware and location diversity based dynamic MCS system. However, these algorithms could not deal with tasks that needed to be completed by multiple workers within a specific period of time. For works on real-time cooperation MCS, Yin et al.[14] studied a time-window based method to manage the emergency task. This method selected idle vehicles when emergency task happened. Chen et al. [15] proposed a crowd tracking system that people can collaboratively kept track of the moving vehicle by taking photographs. [16] proposed a quality-driven auction based incentive mechanism with EM algorithm to guarantee trust. However candidate vehicle is selected in sequence in those methods to form a vehicle set. They lack attention to big scale joint computing vehicle resources for MCS.

B. Blockchain for IoV

Veciles can be connected with RSU via advanced wireless network device[17]. Many methods have been proposed to solve the identity privacy problems associated with the IoV when it is combined with a blockchain. Lu et al. [18] used two types of blockchains to hide the connections between real identities and public keys. Yao et al. [19] implemented cross-data center authentication and allowed users to request changes to their pseudonyms to protect personal privacy. To address the problem of data security, Zhang et al. [21] addressed the challenge of combining the mobile features of the IoV with a blockchain. Kang et al. [20] used a combination of traditional cloud storage and a blockchain to ensure the reliability of data in VANETs. Yue et al. [22] used a consortium blockchain to develop a credit-based data sharing scheme and proposed the use of a three-rights subjective logic model to monitor the sources of data to improve the data reliability. A research[25] has proved entering the blockchain system anonymously guaranteed the user's unconnectability and security to a certain extent.

In summary, existing researches lack a MCS framework which can utilize real-time joint computing power and ensure security protection at the same time. Most of the existing MCS considers to allocate the subtask to a specific vehicle without considering teams, which leads to massive time consuming and cost. In addition, information integration can not be secured in a cental MCS service sometime.

III. System Model and Problem Formulation

In the following, we describe the entities in the model, and explain the design of the functions and services associated with the entities. We then illustrate the crowdsensing process in our model.

A. Entity Definition

The model is designed on a blockchain. The network structure of the model is based on the Internet and a VANET[23]. The model has the following nodes: task issuer node, vehicle node, RSU node, and Personal Certificate Authority(PCA) node.

1) Task Issuer Node: Task issuer nodes are generally organizations or companies with the need for crowdsensing. They register in the blockchain as full nodes to maintain the whole ledger. Task issuers can upload task information to the system, such as completion conditions. Finally, task issuers submit payments to workers via the system.

2) RSU Node: RSU can identify vehicle nodes that are capable of participating in crowdsensing tasks in real time. Each RSU node maintains a table for storing information about teams formed by vehicles in the current time period. When a task is crowdsensed, a smart contract collects information from the RSU nodes to determine the team or teams having the ability to complete the task. When a team is selected, an RSU node receives task information and distributes it to the vehicles in the team, as well as collecting and uploading the results submitted by the vehicles. RSU nodes are also full nodes in the blockchain system and they maintain the blockchain.

3) Vehicle Node: Vehicle nodes are vehicles with a vehicle computer, smart sensors, and network interfaces. All vehicles nodes can communicate with RSU nodes with wireless network[24]. Vehicle nodes can submit their status, willingness to complete tasks, and bidding information to RSUs. They can receive task information from RSUs and submit results to RSUs. Each vehcile node has credit value. We define the node with high credit as formal nodes and the nodes with low credit as informal nodes. In the blockchain system used in our model, vehicle nodes are light nodes registered in the blockchain system because of their poor storing capacity and they have no sufficiently power to generate blocks.

4) PCA: PCA is a management agency responsible for identity verification and registering the nodes in the blockchain system in our model. All the nodes must register with the PCA to be added to the blockchain. And PCA has access to cloud server which can provide complicate computing task and store massive data secretly.

B. BNTC Process

BNTC system shows in Fig. 1.

1) Init System: Nodes with different roles must register in the blockchain system to use the service. To ensure the anonymity and security of all the worker(vehicle node), a certificate is issued by the PCA[25] based on Pointcheval and Sanders(PS-signatures)[26]. The types of nodes in our system are different and the blockchain platform must indicate the roles of the nodes in BNTC by issuing different types of certificates.

2) Crowdsensing Process: The crowdsening process of BNTC is described as follows.

Step 1. An RSU node located at a traffic light sets up network linking the vehicles that enter its road section. The RSU collects information about the vehicles. The information is maintained and refreshed within a certain time period by the RSU.

Step 2. When the task issuer uploads a task for MCS, a deposit is placed in the blockchain to calculate the candidate teams and payment. The platform scans all the RSUs to collect information about the teams and to calculate the most suitable team set for the task by using WTS algorithm for BNTC. The payment for winning set is also calculated in this step based on the credit and bidding price from each vehicle in the team based on the CTP algorithm for BNTC.

Step 3. The winner team set and its payment information are submitted to the task issuers by the system. If the task issuer agrees with the result, the result is signed and the payment is submitted to the system, otherwise the result will be dropped. The blockchain system records the information for the teams, vehicles, RSU, task, task distribution, task issuer, and payment after the result is signed by the task issuer. Each winning RSU distributes subtask to the vehicles in the selected team. After the vehicles complete their task, the result is collected by the RSU. The RSU records the results in the blockchain and sends them to the task issuers at the same time. Smart contracts guarantee that the workers are paid correctly.

C. Problem Formulation

The social welfare should be maximized for the proposed model. Therefore, a satisfaction formula must be defined to measure the welfare for society, and thus, two problems need to be formulated. The first problem involves the manner by which to select one or several appropriate teams for a task according to the task requirements, bidding information, and capability of each vehicle to achieve a high task completion ratio at a low cost. The second problem involves determining an appropriate payment for the selected team to ensure that the incentive is adequate for workers. These two problems both contribute to the social welfare of the system.

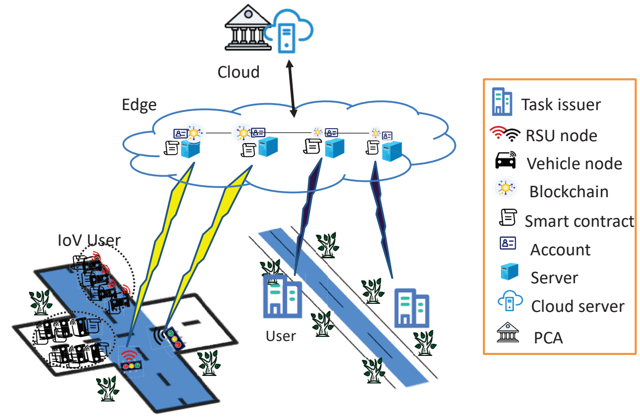

Fig. 1: Framework of BNTC System

IV. ALGORITHM

To solve the problems raised above, we introduced two algorithms for the BNTC system: Winning Teams Selected algorithm and Credit of Teams Payment algorithm for the BNTC model. The main notations used in this system are shown in Table I.

TABLE I: Notations

Notations	Description
V	Existing total vehicular teams
V_{-v}	Existing total vehicular team except team v
S	Scale of task
N	Total number of vehicular teams
v_k	The k^{th} vehicular team
y_k^i	The i^{th} vehicle in the k^{th} vehicular team
tc_k	Number of sub-tasks which vehicle team v_k can complete
q_k^i	Completion Probability of vehicle y_k^i
P_k	Completion Probability of vehicular team v_k
r_k^i	Credit value of vehicle y_k^i
R_k	Credit value of vehicular team v_k
B_k	The average bid of vehicular team v_k
χ	Winning team set of the task
$Cost_\chi$	Cost set of winning team set
$Payment_\chi$	Payment set to winning team set
χ_{-v}	Winning team set of a task excluding team v
A	Number of winning teams

A. Problem Description

The following definitions are required to explain the algorithm. In the entire network, N vehicular teams form a whole team set $V = \{v_1, v_2, ..., v_N\}$. The formal vehicles included in the team v_k are $\{y_k^1, y_k^2, ..., y_k^{m_k}\}$ with a total number of m_k. The informal vehicles are not considered because the low completion rate in their history would lower the predicted probability of completing a task by the team. The completion capacity of a team is defined as $tc_k = m_k * c$, where c is a constant value which denotes the number of subtask one vehicle can complete within a limited time. One task can be divided into A parts, $\{s_1, s_2, ..., s_A\}$. A vehicular teams can complete a task together.

r_k^i is the credit of the vehicle y_k^i. The credit is related to the number of participation and failures. "n" is the total number of participation in tasks by vehicle y_k^i . "m" is the number of failures at task for r_k^i. "ω" is an adjusted parameter to ensure that when a vehicle achieves a success after a failure, its credit will increase to a level lower than that before the failure. More successful completions are required to compensate for previous failures. $flag$ denotes the status of the task result, where 0 indicates a failure and 1 represents success. $(r_k^i)'$ denotes previous credit of y_k^i. Thus, r_k^i is given by

$$r_k^i = \begin{cases} 1 - 0.1m, & n \leq 5, flag = 0 \\ max((r_k^i)' * (1 - \frac{n-m}{n} * \omega), 0), & n > 5, flag = 0 \\ min((r_k^i)' * (1 + \frac{n-m}{n}) * \omega), 1), & n > 5, flag = 1 \end{cases} \quad (1)$$

The initial value can be set as 1. The credit of a vehicular team v_k is given by

$$R_k = (\sum_{y_k^i \epsilon v_k} r_k^i)/m_k. \quad (2)$$

The probability of vehicle y_k^i can be estimated from historical data. Formally, it can be defined as :

$$q_k^i = min((1 + \Delta r_k^i) * q_k^i, 1). \quad (3)$$

Here, we calculate the probability that v_k completes a task is:

$$P_k = 1 - \prod_{y_k^i \epsilon v_k} (1 - q_k^i). \quad (4)$$

Multiple teams can cooperate together to complete a task. The probability of completion for joint teams can be calculated as $\tilde{P}_n = 1 - \prod(1 - P_i)$. When the probability of a team or joint teams completing a task is higher than the requirement of a task, they are considered suitable for the task.

In addition, each vehicle will have a bidding price for a task. The bidding price for a task by a team is the sum of the bidding prices for each vehicle in the team.

B. Problem Model

The completion probability of teams PV is given by

$$PV = \{P_1, P_2, ..., P_N\}. \quad (5)$$

The scale of sub-tasks for each team in a vehicular network of N teams is given by

$$TC = \{tc_1, tc_2, ..., tc_N\}. \quad (6)$$

In the vehicular crowdsensing problem, we consider that the bid of a worker is equal to its cost. The bidding by each team in a vehicular network of N teams to complete a task is given by

$$BV = \{B_1, B_2, ..., B_N\}. \quad (7)$$

The social payment for a task issuer is given by

$$Payment_{issuer} = \sum_{\chi} payment_i. \quad (8)$$

A vehicle can submit its real cost for a task and get proper reward from task issuer. Overpayment ratio(OPR)[12] is the measurement of the reward and a indicator of social welfare. The overpayment ratio is given by

$$OPR = (Payment - Cost)/Cost. \quad (9)$$

Social welfare of this system is given by

$$W_{Social} = \frac{S}{\alpha_1 * Cost + \alpha_2 * OPR * Cost + \alpha_3 * A}. \quad (10)$$

S is the scale of a aim task that needs to be completed. A is the number of winning teams. α_1, α_2 and α_3 are adjustable parameters to ensure the progressive of the three conditions.

The winner team set is given:

$$\chi = \{x_1, x_2 ..., x_A\}. \quad (11)$$

In this model, we need to determined χ to maximize W_{Social} . The following assumptions are required to solve χ.

Assumption 1: The existing vehicular network must be able to satisfy the demand in terms of the number of sub-tasks uploaded by the task issuers. Thus, a task can be crowdsensed by one or several teams.

Assumption 2: The team formed to complete a partial task must remain stable throughout the whole process, so the completion of the work depends only on the task completion probability for each vehicle.

Assumption 3: The bid of a vehicle is its real cost for a sub-task.

Assumption 1 and assumption 2 are easy to meet in practical. Assumption 3 is proved in [16].

C. Winning Teams Selected algorithm for BNTC

Teams or joint teams with a high probability of task completion are selected as the candidate set for a task, thereby improving the task completion rate. Selecting appropriate teams for a task from the candidate set involves minimizing the number of teams to reduce the time consumption by the system and minimizing the total cost for the vehicular teams to satisfy the task issuer. Thus, a satisfaction formula that satisfies the multi-conditional problem is defined and our aim is to select a candidate team based on the satisfaction formula. We define the satisfaction(SAT) formula as follows:

$$SAT = -((a_{min} - a_{max} - 1) * \sum_{\chi} B_i - A) \quad (12)$$

$$= (1 + a_{max} - a_{min}) * \sum_{\chi} B_i + A. \quad (13)$$

where, a_{min} and a_{max} is the boundary value that divides the number of teams.

Proof: First, we consider that the bidding B is constant. A low team number A is better. We define the formula:

$$f(A) = k_1 A \quad s.t. \quad A_1 > A_2, f_1 < f_2$$

Thus, $k_1 < 0$. We simply consider $k_1 = -1$. Similarly, for bidding B, we extend the formula above to the following:

$$g(B, A) = k_2 B - A$$

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We consider that the satisfaction is lower when the cost is higher. When $B_1 > B_2, \forall A_1, A_2 \epsilon [a_{min}, a_{max}]$, we can obtain $g_1 < g_2$.Thus,

$$k_2 B_1 - A_1 < k_2 B_2 - A_2$$

$$k_2 < \frac{A_1 - A_2}{B_1 - B_2}$$

So, we first use the inequality scaling method to obtain

$$k_2 < min(\frac{A_1 - A_2}{B_1 - B_2})$$

We second use the inequality scaling method to get

$$k_2 < a_{min} - a_{max}$$

Simply, we make

$$k_2 = a_{min} - a_{max} - 1$$

We obtain the formula:

$$g(B, A) = k_2 B - A \quad (14)$$

$$= (a_{min} - a_{max} - 1) * \sum_{\chi} B_i - A. \quad (15)$$

We can conclude that the SAT result is always a negative number. Therefore, we reverse it and turn (15) into a positive number in the calculation process as (13). Thus, the satisfaction is greater when SAT is smaller. To solve the problem of selecting teams χ for tasks, we propose a knapsack-based algorithm called winning teams for the BNTC algorithm. In BNTC algorithm, the dynamic state transfer function is to get the minimum value which denotes the maximum satisfaction at that aim scale task. We use array SA to denote the status of SAT in the procedure of dynamic transfer,

$$SA[j] = min(SAT(SA[j - TC[i]], TC[i]), SA[j]) \quad (16)$$

where, j denotes the task scale. When the task scale is $j - TC[i]$ and team i is selected, the task scale is $j = (j - TC[i]) + TC[i]$, the satisfaction function of scale j is $SAT(SA[j - TC[i]], TC[i])$. We update $SA[j]$ with the minimum value between $SAT(SA[j - TC[i]], TC[i])$ and previous $SA[j]$.

The pseudo code is shown as Algorithm 1. Task scale S, candidate teams count N, bids set $BV[N]$ and team capacity $TC[N]$ are input while winning team set χ is output. We need traverse from 0 to N. We calculate from scale S to the scale$TC[i]$ of team i. The satisfaction of every team scale is calculated until the minimum value which denotes maximum satisfaction of that scale is achieved.

The time complexity of the algorithm is $O(SN)$. Using the idea of dynamic programming, the knapsack algorithm can directly determine the optimal result that satisfies the completion of a certain number of tasks.

Algorithm 1 Winning-Bid Selection Algorithm

Input: S,N, $BV[N]$, $TC[N]$
Output: $value$, $nums$, χ
$WinningTeamSet \leftarrow []$
$nums \leftarrow 0$
for $i = 0$ to N **do**
  for $j = S$ to $TC[i]$ **do**
    $bs \leftarrow SAT(SA[j - TC[i]], TC[i])$
    if $SA[j] > bs$ **then**
      $SA[j] \leftarrow bs$
      $WinningTeamSet[j] \leftarrow WinningTeamSet[j - TC[i]] \cup i$
    end if
  end for
  $i \leftarrow i + 1$
end for
for i in $WinningTeamSet[S]$ **do**
  $value \leftarrow value + B[i]$
  $nums \leftarrow nums + 1$
end for
$\chi \leftarrow WinningTeamSet[S]$
return $value$ and $nums$ and χ

D. Credit-based Team Payment algotirhm for BNTC

In this section, we discuss how to determine the rewards for selected teams with CTP algorithm for BNTC. To guarantee the fairness of each team, we pay team x according to its credit and extern pricing which is calculated by utility and overall utility of another best candidate team set with x excluded. When a task can't be completed without team x, team x is regarded as "Critical Team". When a task can be completed without team x , team x is regarded as "Ordinary Team" First, we define the utility of a team x for the sub-task as $Utilv$:

$$Utilv = TC_x / B_x. \quad (17)$$

We define average utility value of a new winning set without team x as $eUtilv$:

$$eUtilv = S / \sum_{v \epsilon \chi_{-x}} B_v. \quad (18)$$

Thus, we determine the payment to winner team x as Pay_x. If x is an "Ordinary Team", we pay x as (19). If it's a "Critical Team", we pay x as (20).

$$Pay_x = tc_x((1/eUtilv + 1/Utilv_{min})/2 + (R_0 - R)^2) * \varphi \quad (19)$$

$$Pay_x = tc_x * (1/Utilv_{min} + (R_0 - R)^2) \quad (20)$$

where, R_0 is the benchmark value of the reward. φ is an adjustable parameter for reward. The description of this algorithm is listed in Algorithm 2.

We need to give a price to each vehicle in the network team and each price must be calculated by recalculating the allocation. Thus, the time complexity is: $O(A * S * (N - 1)) = O(ASN)$.

Algorithm 2 Rewards Payment Algorithm

Input: S, N, $BV[N]$, $TC[N]$, χ
Output: Reward $Payment_{\chi}$

for all $x \epsilon \chi$ **do**
  $TC \leftarrow TC_{-x}$
  $BV \leftarrow BV_{-x}$
  if $CriticalTeam$ **then**
    $payment_x \leftarrow eq.(20)$
  end if
  recalculate winning set result without x as $\chi_{-x}, value_{-x}, num_{-x}$ by Algorithm 1
  select $Utilv_{min} = minimum(Utilv)$ from χ_{-x}
  $payment_x \leftarrow eq.(19)$
end for
return $Payment_{\chi}$

V. EVALUATION

In the following, we introduce the experimental environment and the dataset employed. We first experimentally evaluate WTS algorithm and CTP algorithm for BNTC, as described in the previous section, and analyze the experimental results. Then we evaluate resource consumption of BNTC in blockchain.

A. Dataset and Experimental Design

We mainly conduct simulation experiments. We simulate the status of different users for bidding tasks. We use the dataset of [27] in Bologna, Italy. This dataset collected road vehicle information from 8 am to 9 am a day. The road map of the dataset is shown in Fig.2. When a congestion occurs at an intersection, a vehicular network team is formed by RSU(more than 10 vehicles). We assume all the vehicles on road are able and willing to participate in conducting crowdsensing tasks. And all data submitted by vehicles are reliable.

TABLE II: Initialization of Major Parameters

Parameters	Initialization
Credit of a vehicle	1.0
Initial probability of a vehicle	0.8
Require probability δ	0.5
Cost coefficient range	[1,1.5]
ω	0.5
α_1, α_2, α_3	0.7,0.2,0.1
R_0,φ	0.5,10

B. Experiment Result

We use the following metrics to evaluate the performance of our system: social welfare, social cost of team workers[16], social cost of task issuers(payment), the overpayment ratio, and number of winning teams. The baseline algorithms in this experiment were MCBS [12] and the DQDA algorithm [16] in the EM algorithm for evaluating the data quality.

The initial settings of the simulation are shown in Table II. α_1, α_2 and α_3 are parameters representing the weight of cost, overpayment and account of winning teams in our model. We

Fig. 2: Map of Bologna area.

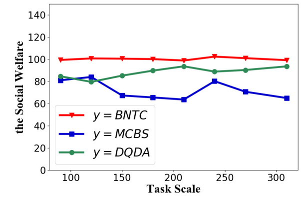

Fig. 3: Social Welfare of the System.

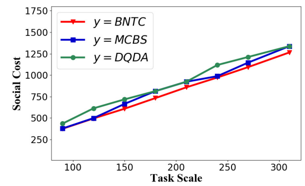

Fig. 4: Social Cost of the System.

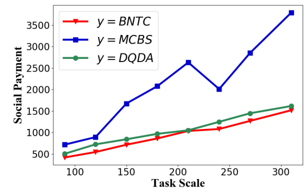

Fig. 5: Social Payment of the System.

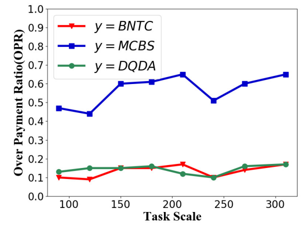

Fig. 6: Over Payment Ratio of the System.

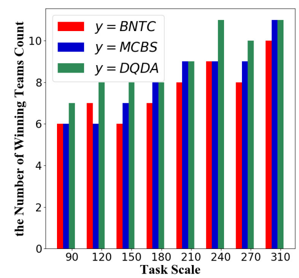

Fig. 7: Number of Winning Teams of the System.

init them based on the concerns of maximize social welfare. R_0 is base credit set by PCA. ω and φ are parameters to adjust payment to each vehicle and can be initialized by experience.

1) Social Welfare: The social welfare results are shown in Fig. 3. The social welfare is measured using the satisfaction formula. The social welfare is largest with BNTC among the three algorithms.

2) Social Cost: In the case of different workloads, the costs for all workers with each algorithm are shown in Fig. 4. The results indicate that the cost increases and the task issuer needs to pay more as the task scale increases. As shown in Fig. 3, the cost of the BNTC algorithm is always the smallest under the same condition and the knapsack algorithm could obtain the optimal solution in a distribution.

3) Social Payment: The task issuer pay rewards to the selected team. The results indicate that the total payment is highest with BNTC among the three algorithms under the same condition. The payment increases with task scale. The mechanism employed by MCBS is similar to that used by BNTC. However, MCBS considers the utility ratio rather than scale. The results are shown in Fig. 5.

4) Overpayment Ratio: The experiment on the overpayment ratio demonstrates that the overpayment ratio is not correlated with the scale of tasks. MCBS still lead to high

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overpayment ratio due to its external prices mechanism. In some case(task scale 210), the over ratio of DQDA is the best. The payment are more approximative with real cost. But it suffers high cost and payment problems. The results are shown in Fig. 6.

5) Winning Team Count: The numbers of teams selected for a task are shown in Fig. 7. BNTC performs better than the baseline methods in most situations. However, BNTC is not a greedy algorithm. Thus, it might not have performed as well as MCBS according to this indicator.

The experiments show that BNTC performs better than the baseline methods in terms of most of the indicators. The satisfaction formula shows that BNTC could achieve the minimum payment and cost, and the maximum social welfare. Compared with the other two methods, BNTC has the lowest social cost and lowest payment. Since overpayment ratio is inversely correlated with the social cost, so BNTC tends to yield a high overpayment ratio in some cases. Above all, BNTC is more effective than baselines.

6) Credit For BNTC: Simulations for overpayment ratio of a teamset is shown in Fig.8. With a larger credit value, a team is likely to get a higher pay for its work.

A vehicle will get a heavy penalty for failures(e.g. malicious actions). It will take more successful actions to get back to its previous normal credit value. Simulation results is shown in Fig.9.

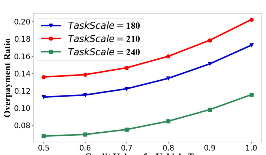

Fig. 8: Overpayment ratio with Change of Credit.

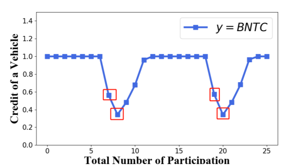

Fig. 9: Change of Vehicle Credit because of Failure(eg.malicious operation).

C. Resource Consumption Evaluation

1) Registration Performance: PCA generates an anonymous certificate for each vehicle node and key pair for RSU node and task issuer node. We evaluate the performance for certificate and key pair generation in Golang off-line. Results show the time consumption is acceptable, as shown in Table III.

TABLE III: Generation Time

Operations	Entities	Time(ms)
Certificate	Vehicle Node	166
Key Pair	RSU node and Task Issuer Node	27

2) Smart Contract Performance: We build an Ethereum priavate chain with a PC and five Raspberry Pies for simulation. PC is regarded as task issuer. RSU services and data are loaded into Raspberry Pies. In order to show the performance of WTS algorithm and CTP algorithm for BNTC in smart contract, we use gas model of Ethereum to measure the cost of each function of the algorithms. We set the gas price as 0.000000001 (1 Gwei) Ether per gas as in [16]. The price of each Ether is around 141.53$ on April 1st in 2020. The two algorithms only cost 1.419$(0.2304+1.189) to get distribution and payment result. The resource consumption is within a reasonable range.

VI. Conclusion

In this study, we propose a nondeterministic vehicular team task model to efficiently utilize the joint computing power of numerous vehicles in cities. Our model employs team cooperation to ensure the completion of crowdsensing tasks. The model runs on the blockchain platform and smart contracts can guarantee the security of the system. Based on the reverse auction method, we propose WTS algorithm and CTP algorithm for the BNTC to maximize the social welfare and minimize the time consumption. Theoretical analyses and extensive simulations demonstrate that the proposed model performs better than the baseline methods and it achieves the maximum social welfare. At last, implementation with Ethereum suggests our model can operate within a reasonable cost.

References

[1] D. Yu, Y. Zou, J. Yu, Y. Zhang, F. Li, X. Cheng, F. Dressler, F. C.M. Lau, "Implementing Abstract MAC Layer in Dynamic Networks," IEEE Trans. Mobile Comput., 2020.

[2] T. Qiu, J. Liu, W. Si and D. Wu, "Robustness Optimization Scheme with Multi-population Co-evolution for Scale-free Wireless Sensor Networks," IEEE/ACM Trans. Networking, vol. 27, no. 3, pp. 1028-1042, 2019.

[3] D. Niyato and E. Hossain, "A Unified Framework for Optimal Wireless Access for Data Streaming Over Vehicle-to-Roadside Communications," in IEEE Trans. Veh. Technol., vol. 59, no. 6, pp. 3025-3035, 2010.

[4] T. Liu, Y. Zhu, Y. Yang, F. Ye, "ALC^2: When Active Learning Meets Compressive Crowdsensing for Urban Air Pollution Monitoring," IEEE Internet of Things J., vol.6, no. 6, pp. 9427-9438 ,2019.

[5] L. Wang, Z. yu, D. Yang, H. Ma, H. Sheng, "Efficiently Targeted Billboard Advertising Using Crowdsensing Vehicle Trajectory Data," IEEE Trans. Ind. Informat., vol. 16, no. 2, pp. 1058-1066, 2020.

[6] Y. Lu, X. Huang, K. Zhang, and S. Maharjan, "Blockchain Empowered Asynchronous Federated Learning for Secure Data Sharing in Internet of Vehicles," IEEE Trans. Veh. Technol. 2020.

[7] Z. Feng, Y. Zhu, Q. Zhang, L. Ni and A. vasilakos, "TRAC: Truthful auction for location-aware collaborative sensing in mobile crowdsourcing," IEEE INFOCOM, 2014.

[8] D.Yang, G.Xue, X.Fang and J.Tang, "Incentive mechanisms for crowdsensing: Crowdsourcing with smartphones," IEEE/ACM Trans. Netw., nol. 24,no. 3, pp. 1732-1744, 2015.

[9] H. Jin, L. Su, and K. Nahrstedt, "CENTURION: Incentivizing multi-requester mobile crowd sensing," IEEE INFOCOM, 2017.

[10] T. Qiu, B. Li, W. Qu, E. Ahmed and X. Wang, "TOSG: A topology optimization scheme with global-small-world for industrial heterogeneous Internet of Things," IEEE Trans. Ind. Informat., vol. 15, no. 6, pp. 3174-3184, 2019.

[11] L. Wang, Z. Yu, D .Yang, "Collaborative Mobile Crowdsensing in Opportunistic D2D Networks: A Graph-based Approach ," ACM, trans.sensor networks. vol. 15, no. 3, 2019.

[12] C. Hu, M. Xiao, L. Huang and G. Gao, "Truthful Incentive Mechanism for Nondeterministic Crowdsensing with Vehicles," IEEE Trans. Mobile Comput., 2018.

[13] X. Wang, R. Jia, X. Tian, "Location-Aware Crowdsensing: Dynamic Task Assignment and Truth Inference," IEEE Trans. Mobile Comput., vol. 19, no. 2, 2020.

[14] B. Yin, Y. Wu,T. Hu, "An Efficient Collaboration and Incentive Mechanism for Internet of Vehicles (IoV) With Secured Information Exchange Based on Blockchains," IEEE Internet of Things J.,vol.7, no. 3, pp. 1582-1593, 2020.

TABLE IV: Resource Consumption Evaluation

Algorithm	Function	Description	Transaction Cost(gas)	Execution Cost(gas)	Total Cost(gas)	Dollar
Initialization	Init()	Initial smart contract	3155990	2351810	5507800	0.3748
Add Team	AddTeam()	Collect candidate teams.	195379	172315	367694	0.0515
Set Task Issuer	SetCall()	Set task issuer address.	65372	42180	107552	0.0151
Check Info	CheckTeams()	Get team information.	85837	64565	150402	0.0211
Set Aim Task	SetTaskAim()	Set aim task scale.	42601	21137	63738	0.0089
WTS Algorithm	getWinnerTeam()	Get winner team set.	1496032	1493960	2989992	0.2304
CTP Algorithm	getPayment()	Get payment for winner team set.	4180347	4312675	8493022	1.1890
Bulk Transfer	Transfer()	Transfer for each winner team.	39691	14643	54334	0.0076

[15] H. Chen, B. Guo, Z. Yu, "CrowdTracking: Real-Time Vehicle Tracking Through Mobile Crowdsensing," IEEE Internet of Things J., vol. 6, no. 5, pp.7570-7583, 2019.

[16] W. Chen, Y. Chen, X. Chen and Z. Zheng, "Toward Secure Data Sharing for the IoV: A Quality-Driven Incentive Mechanism with On-Chain and Off-Chain Guarantees," IEEE Internet of Things J., 2019.

[17] D. Yu, Y. Zou, J. Yu, X. Cheng, Q. Hua, H. Jin, F. Lau. "Stable Local Broadcast in Multihop Wireless Networks Under SINR," IEEE/ACM Trans. Networking, vol. 26 no. 3, pp. 1278-1291, 2018.

[18] Z. Lu, Q. Wang, G. Qu and Z. Liu, "BARS: A Blockchain-Based Anonymous Reputation System for Trust Management in VANETs," IEEE Internet Conf. Trust, Security Privacy Comput. Commun./ 12th IEEE Int. Conf. Big Data Science Engineering (TrustCom/BigDataSE), New York, NY, pp. 98-103, 2018.

[19] Y. Yao, X. Chang, J. Mišić, V. B. Misic and L. Li, "BLA: Blockchain-Assisted Lightweight Anonymous Authentication for Distributed Vehicular Fog Services," IEEE Internet of Things J., vol. 6, no. 2, pp. 3775-3784, 2019.

[20] D. Liu, A. Alahmadi, J. Ni, X. Lin and X. Shen, "Anonymous Reputation System for IIoT-Enabled Retail Marketing Atop PoS Blockchain," IEEE Trans. Ind. Informat., vol. 15, no. 6, pp. 3527-3537, 2019.

[21] L. Yue, H. Junqin, Q. Shengzhi and W. Ruijin, "Big Data Model of Security Sharing Based on Blockchain," Internet. Conf. Big Data Comput. Commun.(BIGCOM), Chengdu, pp. 117-121, 2017.

[22] J Kang, R Yu, X Huang, M Wu, S Maharjan, S Xie and Y Zhang, "Blockchain for Secure and Efficient Data Sharing in Vehicular Edge Computing and Networks," IEEE Internet of Things J., vol. 6, no. 3, pp. 4660-4670, 2019.

[23] N. Chen, T. Qiu, X. Zhou, K. Li and M. Atiquzzaman, "An Intelligent Robust Networking Mechanism for the Internet of Things," IEEE Commun. Mag., vol. 57, no. 11, pp. 91-95, 2019.

[24] D. Yu, L. Ning, Y. Zou, J. Yu, X. Cheng, F. Lau, "Distributed Spanner Construction With Physical Interference: Constant Stretch and Linear Sparseness," IEEE/ACM Trans. Networking, vol. 25, no. 4, pp. 2138-2151, 2017.

[25] D. Liu, A. Alahmadi, J. Ni, X. Lin and X. Shen, "Anonymous Reputation System for IIoT-Enabled Retail Marketing Atop PoS Blockchain," IEEE Trans. Ind. Informat., vol. 15, no. 6, pp. 3527-3537, 2019.

[26] D. Pointcheval and O. Sanders, "Reassessing Security of Randomizable Signatures," in Proc. Cryptograph Track RSA Conf., pp. 319-338, 2018.

[27] L. Bedogni, M. Gramaglia, A. Vesco, M. Fiore, J. Harri and F. Ferrero, "The Bologna Ringway Dataset: Improving Road Network Conversion in SUMO and Validating Urban Mobility via Navigation Services," IEEE Trans. Veh. Technol., vol. 64, no. 12, pp. 5464-5476, 2015.

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