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Bargaining based Design Mechanism for delay sensitive tasks of mobile crowdsensing in IoT

Waqas Ahmad[a], Ata Ullah[b], Sheharyar[a], N.Z. Jhanjhi[c,*], Rania M. Ghoniem[d], Sarfraz Nawaz Brohi[e]

[a] *College of Information Science and Technology, Beijing Normal University, Beijing 100875, China*
[b] *Department of Computer Science, National University of Modern Languages (NUML), Islamabad 44000, Pakistan*
[c] *School of Computer Science SCS, Taylor's University, Malaysia*
[d] *Department of Information Technology, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia*
[e] *Computer Science and Creative Technologies, University of the West of England, Bristol BS16 1QY, UK*

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Abstract

Internet of Things (IoT) is getting growing interest to offer great opportunities in combination with Mobile Crowd Sensing for real-time applications. Existing approaches motivate mobile workers (MWs) for approaching the distant locations to receive attractive incentives for traveling. The main question addressed is that a number of tasks remain incomplete out of total al-located tasks. Moreover, the profitability and feasible budget constraints of the platform is also not considered. This paper presents Bargaining based Design Mechanism (BDM) to involve the nearest located MWs to improve the completion of tasks. The main method involves a bargaining based game model that increases the task completion ratio while considering the feasible budget constraint, platform profitability and social welfare. The proposed approach comprises of two algorithms: one for the selection of optimal MWs with low cost and less delay. Second is to organize bargaining for rewarding the platform on social welfare. Our work is validated by developing a testbed on Windows Azure cloud. Results prove that proposed BDM out-performs the counterparts in terms of decay coefficient, task completion ratio, participant's winning ratio, fraction of task incompletion and social welfare.

Keywords: Mobile Crowd Sensing (MCS); IoT; Game theory; Design mechanism

1. Introduction

Internet of Things (IoT) comprises of a large number of devices that collaborate with each other to share information among different smart devices across the networks [1]. Mobile Crowd Sensing (MCS) is an enhanced mobile computing scenario to fetch and offer services to the subscribers [2]. A key application of MCS is in transportation services like online cab service where a large number of drivers and passengers interact to avail services. Moreover, MCS is also applicable in user's behavior analysis and path planning for drones [3]. In MCS, the MWs are involved to perform tasks who may cooperate to perform one single task as per level of quality and security demands [4]. It helps to achieve classification of task, division of task, allocation of task, and the evaluation of task quality [5,6] with attractive incentive mechanisms which also involves the game theory for assigning tasks after identifying the role of MWs [7,8] for active participation of MWs. The reputation aware recruitment [9] is mandatory to identify the reliable MWs along with privacy of contributors [10] for user satisfaction. Moreover, it involves feasible budget centric measures [11], platform and MW centric models [12] by offering social admiration and monetary reward [13].

Game theory is involved for bargaining the reward of MWs for the assigned task. The real scenario for rewarding the MWs can be in case of the drivers who are paid the fare and the incentives from the riding company as well where a huge number of passengers are served for a massive number of tasks. The game players adopt strategies which can maximize the platform utility for tasks. The main goal is to establish an

* Corresponding author.
E-mail addresses: waqasmsiiui@yahoo.com (W. Ahmad), aullah@numl.edu.pk (A. Ullah), sheheryar91@yahoo.com (Sheharyar), noorzaman.jhanjhi@taylors.edu.my (N.Z. Jhanjhi), rmghoniem@pnu.edu.sa5 (R.M. Ghoniem), sarfraz.brohi@uwe.ac.uk (S.N. Brohi).
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optimum level so that profit can be maximized or loss can be reduced. Nash Bargaining Solution (NBS) ensures profit maximization. For a better estimation of MW's cost and loyalty for the task, the MWs' mobility routine should be predicted [14]. Nash equilibrium is used for non-cooperative games which ensure that no regret situation occur for the game players in the absence of law enforcement authority [15]. To the best of our knowledge, we are the first one to consider the bargaining game for MW and platform especially for time-sensitive task scenarios in MCS.

This paper presents a game theory based bargaining solution for the design mechanism to enhance the resource utilization. This work aims to minimize the distance for time sensitive tasks by using game theory where a bargaining game is proposed between platform and MW. The main contributions of the work are enumerated as follows:

(1) We present the selection for MWs who are close to the task location and then perform game based bargaining on bids as per traveling cost and time involved for the task.
(2) We proposed a novel NBS based optimization algorithm to manage task handling criteria as per nature of task.

Rest of the paper is organized as follows: Section 2 explores the literature review and Section 3 explores system model and the proposed BDM system. Results are illustrated in Section 4. Section 5 concludes our work.

2. Literature review

In this Section, we focused on the MW selection mechanisms that utilize gaining mechanisms for incentivizing on the basis of certain tasks. We considered delay tolerant and time sensitive tasks along with mobility based un-even distribution in MCS along with game based solutions.

2.1. Time-sensitive tasks based approaches

It identifies the task completion capacity and movement to identify minimum distance between the task location and the MWs [16]. In [17], the competition of MWs is considered for certain tasks, The MWs decide on the basis of a congestion game theory. It helps to improve the confidence level on the system by providing a fair competition without involving a massive inclusion of MWs for a single task. It also identifies a route to perform the task for each MW. The stable task allocation in [18] uses the budget constraints to select the suitable MWs and willingness to move towards the task region. Furthermore, a stable matching algorithm was designed to select MW and respective incentives. In time-sensitive incentive-aware (TSIA) scheme, two-player cooperation is considered like data collectors and a mobile user to send the sensed data back to requester through platform. The data collector performs task and rely on mobile user for its transmission where data must be delivered with cooperation of game players [19]. The selfish and cooperative scheme involves TSIA for selfish model using greedy approach and TSIA for cooperative setting where the task is accepted without considering MW's utility. In this case, MW is an intermediate relay user instead of requester. In our work, we considered MW's utility to enhance the performance.

The Bayes Nash involves a regulator as an authority responsible for necessary settings to achieve unique NBS. In [20], NBS demonstrates the acceptable and rejectable range of values for the platform and the MW. For any task, if utility W_u is less than the unit cost c_i, then MW will not perform the task due to no payoff. If cost of the platform C_P is higher than the maximum surplus MP or total surplus TP from task, then the bargaining game ends up on disagreement. To avoid complexity of dealing with multiple equilibria, we consider bargaining power up to two stages. We also consider bargaining directly between MW and the platform in contrast to [16] where the feasible budget of the platform was neglected.

2.2. Spatial crowdsensing based approaches

The distance from task location is critical for MWs to move on the best trajectory in limited area. It can be useful for identifying the coverage for stable task allocation [21]. This approach is a bit similar to our work as we also recruit workers who may perform more than one tasks. It enhances platform utility where MWs earn more with multiple tasks. In Movement Based Incentive (MBI) scheme, an un-even distribution of MW in urban and rural areas is experienced to increase profitability. In this scheme, the completion of task is paid whole attention while other important aspects are ignored like feasible budget, platform profit and delay-sensitive nature of tasks [22]. A time based task allocation [23] highlights that MW has dependency on available time to do certain tasks. The scheme presents the efficient allocation mechanism in a time-specific slots to enhance working capacity and chances for task completion. In [24] the trajectories of the MWs are considered to decide about task allocation. It prefers of the MWs in region of the task. It enhances the chances of task completion in variety of tasks occurrences in different regions. In [25], the traveling effort of MW is considered to perform tasks. The maximum number of MWs to perform a single task is predefined to guarantee the decrease in error measurement and enhance profit for platform. Our proposed scheme is limited to delay-tolerant tasks (see Table 2).

2.3. Prediction based approaches

For delay-tolerant tasks prediction based approaches can exploit routine of MWs (from history) whereas, for the time sensitive tasks delay is not affordable. Mobility prediction model has been used in [26] to get probabilistic utility of workers and for the selection of suitable workers. Time-related Markov model is used to fetch probabilities. Another prediction based approach is proposed in [27]. It categorized the users in two categories including Pay As You Go (PAYG) and Pay As You go Monthly (PAYM). The users in PAYM have larger contact probability. Semi Markov model is used for probability distribution of users to come at a Point of

Table 1
List of notations for BDM.

Notation	Description
P_u, W_u, S_w	Utility of platform and MWs, Social welfare
$P_{u,A}$, $P_{u,D}$	Utility of platform over agreement or disagreement
$W_{u,A}$, $W_{u,D}$	Utility of MW over agreement or disagreement
b_i, b_{ij}	Bid of a MW$_i$ for task i and bid of MW$_i$ for task j
α_P^T, α_M^T	α_P^T, α_M^T are bargaining powers of platform and MW
T, t_i *or* $\tau_i \varepsilon T$, D_t	Task T, Subtasks of $T = \{\tau_1, \tau_2, \tau_3 \dots \tau_n\}$ and τ_i is the deadline of task completion
$M_{ds} \leq M$, δ, d_s	Maximum mobility budget of MW. d_s is distance of MW from sensing location, δ is discount factor
N, N_c	Total number of MWs, N_c: Candidates with bid*s,*
N_{RC}, N_{SC}	Set of real candidates to selected and bargain
S_r, $l_i \varepsilon L$	S_r is sensing report, $l_i \in L$ = [lati., longi.] is a sensing location from a set of locations
c_i, C_i,	c_i is the unit cost paid to the MW whereas C_i is the total cost paid to one $MW \in N_w$

Table 2
Algorithms for selection of MW and bargaining solution.

Algorithm 1: Selection of MW for optimal NBS.

Input: $T = \{\tau_1, \tau_2, \tau_3 \dots \tau_n\}$, $B = \{b_1, b_2, b_3 \dots b_n\}$, D=30
Output: N_{RC_i} // list of MWs as real candidate

1. Initialization: $N_{RC_1} = \Phi$, $N_{RC_2} = \Phi, N_{SC_i} = \Phi$
2. **For** all $b_i \in B$
3. **If** $d_i > D_i$ **then** $N_{RC_1} \leftarrow (N_{RC_1})\text{U}(C_\text{i})$
4. **Else** $N_{RC_2} \leftarrow (N_{RC_2})\text{U}(C_\text{i})$
5. **End If**
6. **End For**
7. **For** any $C_i \in N_{RC_2} \| N_{RC_1}$
8. $C_i = \arg max_{b_i \in B \setminus N_{SC}} S_w(U_i \in U, N_{SC_i})$
9. **If** $S_w\left(C_i \in U, N_{SC_i}\right) \leq 0$ **then** BREAK **End If**
10. **End For**
11. **If** $N_{RC_i} \neq \Phi$ && $N_{SC_i} \neq \Phi$ **then**
12. Based on $(\alpha_T^{N_{RC_i}}, \alpha_T^P)$, apply optimized NBS using Algorithm 2
13. **End If**

Algorithm 2: Optimized Nash bargaining Solution.

Input: Set of N_{SC}, $\text{t} = 0/1$
Output: Winner (N_W), P_u, W_u, S_w

1. $N_{Int.(i)} \in N_{SC} = \Phi, N_{del.(i)} \in N_{SC} = \Phi$ //Similar interest of MWs $N_{Int(i)}$, $N_{del.(i)}$ is set of MWs with same delay and $N_{SC} \in N_{RC2}$
2. Sort $N_{Int.(i)}$ in descending and $N_{del.(i)}$ in ascending order
3. **If** (t = 0) **then** // delay-tolerant task
4. **For** i=1 to $|N_{Int.(i)}|$
5. Select MW_i of highest interest, offer $P_{offer(1)}$
6. Update P_u, W_u, S_w Go To For
7. **If** $(C\_off = True)$ **then** //counteroffer by MW_i
8. Evaluate $\mathbb{E}(P_u, S_w)$ // utility & social welfare
9. **If** $(C\_off > P_{offer(1)})$ && $|N_{Int.(i)}| > 1)$ **then**
10. Reject MW_i, Set $D = 0$, Go To For at Step 16
11. **Else** $P_{offer(2)} = P_{offer(1)} + c$ //c is constant
12. **If** $(D = 1)$ **then** Update P_u, W_u, S_w **End If**
13. **End If**
14. **End If**
15. **End For**
16. **Else**
17. **For** i=1 to $|N_{del.(i)}|$ //delay-sensitive task
18. Select MW_i of lowest distance, platform offer $P_{offer(1)}$
19. **If** $(D = 1)$ **then** Assign task to MW_i, Update P_u, W_u, S_w
20. **Else** $P_{offer(2)} = P_{offer(1)} + c$ //c is constant amount
21. **End If**
22. **If** $(D\,!= 1)$ **then** Go To For //offers level 2 **End If**
23. **End For**
24. **End If**

Interest where MWs are recruited through cost prediction but with chances of inaccuracy. In movement-based approaches, optimization of platform's profit is neglected and more attention is given to task completion [27]. In vehicle based task assignment, a truck based task assignment is presented to launch a UAV to perform the assigned tasks. The vehicle plays a role for mobile task execution and the networking facility to connect with UAVs. It also involves the joint tasks with neighboring vehicles to plan the path towards the assigned area [28]. These real application scenarios can be enhanced with the server less computing to supports edge node with scarce resources. It involves the use of cold start deployment mode with less resource utilization [29].

3. System model and proposed methods

We present a Bargaining Based Design Mechanism (BDM) to enhance the task completion ratios for time sensitive tasks. We resolved the problem of the incompletion of tasks due to uneven distribution where profitability and feasible budget constraints are also ignored for the platform. Moreover, the minimum traveling distance of MWs from the task location was not considered for these tasks. This work used the bargaining game based model between platform and MW for enhancing the completion of tasks where Nash based solution negotiates on surplus share. Our work optimizes platform utility and social welfare. A list of notations is presented in Table 1.

3.1. System model

Fig. 1 illustrates the proposed BDM architecture to show interaction between tasks and platform. In the step1, task is offered by the platform for the payment p_1, p_2 offered to the MW with required capabilities for the task. In Step 2, MW responds with the bidding values where v_1 is lower and v_2 is higher. In step 3, platform may offer any one option; (i) p_1 shows a case when platform offers low value for the announced task. It takes the risk for either agreement or disagreement E(A/D). (ii) p_2 is vice versa of p_1. (iii) term $(\frac{\text{p}_2}{2})$ shows a case when platform has high priority of a task but offers half value. In Step 4, MW shares low and high values as v_1 and v_2 for bidding. In Step 5, platform may proceed to step 6 to assign the task. Otherwise, repeat from the step 1 to select another MW from the list.

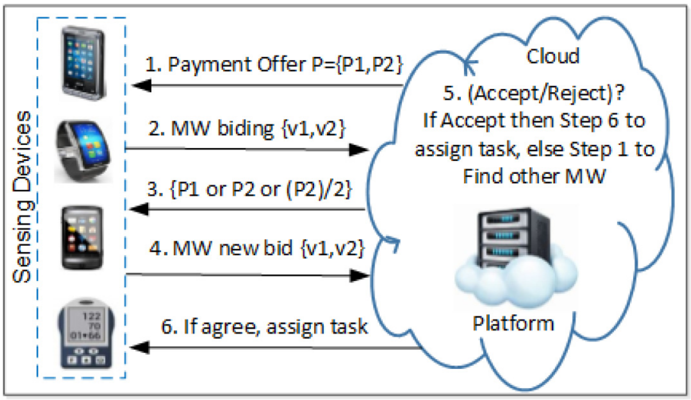

Fig. 1. Proposed system model of BDM.

3.2. Design mechanism

The DM represents the model to select the MWs and pay the amount. It is shown as $M\ (f, g)$ where f is set of possible MWs and g is a payment after bargaining when the game ends. The set of MWs is $U = \{u_1, u_2, u_3, \ldots, u_n\}$ and set of tasks is $T = \{\tau_1, \tau_2, \tau_3 \ldots \tau_n\}$ where $n\varepsilon N = \{1, 2, 3, \ldots, N\}$. It is assumed that MWs perform tasks under game-theoretic setting. The DM categorizes MWs on the basis of function $f(b_i, D_s)$ where b_i is the bid of a MW and D_s represents the distance to task location l_i. The MWs having lowest bid shortest distance will be considered. The MW shares a bid $b_i = (c_i', d_s, \eta_i, \mathrm{t}_i)$ where is c_i' announced cost, $i\varepsilon U$, d_s is the distance of MW_i from task location as $\sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$, η_i is the cost of movement and t_i is the expected delay in reaching the task location. The expected delay is one of the benchmarks to recruit a MW. We check the delay t_i for the delay-sensitive task.

3.3. Selection of suitable MWs

The proposed model considers two players in a bargaining situation to deal with the division of surplus earned after the task. It is also critical to choose a suitable MW for delivery of task within time constraint. The discount factor $0 < \delta < 1$ decreases it as $(W_u{*}\delta)$ for MW and $(P_u{*}\delta)$ for platform. At first stage during surplus sharing, a bid diminish the payoff δ_{b_2} for MW and $\delta(1 - y)$ for DM, where y is the reply bid of MW. Here b_2 for MW_i can be the surplus MP for the time-critical tasks. If the value of δ is very high, then MW_i can easily reject the bid/offer. On the contrary, DM holds a large amount of the total surplus over MW_i. In that case, MW_i would move forward for counteroffer that may decrease the task valuation in time-sensitive tasks. Initially, the distance is calculated among the MWs and tasks. MWs near to the task location may require less effort and movement cost.

Algorithm 1 is aimed at the selection of a MW. Inputs to the algorithm are the set of tasks T and bids B of MWs for the tasks announced by the platform. The output is the list of MWs that are real candidates represented as N_{RC_i}. In the steps 2 to 8, MWs are categorized based on the distance from task location as per the specified threshold D_i. Next, the distance of MW from the task location is calculated and then listed in N_{RC_1}or N_{RC_2} which are considered as the lists of real candidates. These are candidate MWs that are located near the task position and whose bids are not exceeding the total earning from the task. In steps 9 to 14, bids of MWs are evaluated for any candidate from C_i belonging to N_{RC_1}or N_{RC_2}. It verifies social welfare $S_w(U_i \in U, N_{SC})$ and break the iteration. It involves the optimization of social welfare for every C_i. This is calculated for any C_i until S_w cannot be improved further and selects suitable candidates.

3.4. Optimized Nash bargaining solution

Incentives of task completion in MCS are not very high especially for small tasks. It is quite challenging to motivate MWs to perform tasks. In this scenario, random task allocation causes uncertainty of task completion due to its location variations. To ensure the NBS, complete information of task must be provided for bargaining in a game model as per set belief. By considering P_0 and Q_0 be lower and upper cost for the initial beliefs of the platform about MWs. The values may be taken from history which can set the ground for the refinement of belief after bargaining sessions. It would be helpful to categorize. The MW is considered weak whose bid is near to the expected real cost of task completion and vice versa. Secondly, the interest level can be decided based on the strength of bid. Thirdly, the bargaining power is decided as per the time sensitivity. For delay tolerant task, the platform will have more bargaining power. Bargaining power of a MW is represented as (α_M^T) which can vary from worker to work even for the same MW when performing a second task. The MW who is more interested in performing the task will have low bargaining power and vice versa. Bargaining power of MW and the platform is in the interval of $\left(\alpha_P^T, \alpha_M^T\right) \varepsilon[0, 1]$. Next, we describe stepwise execution of algorithm 2. The output of the algorithm includes utilities P_u and W_u for platform and MW, respectively. Moreover, social welfare S_w is also generated to report the performance. In Step 2, the interest levels in MWs' list is sorted in descending order to find the MW with maximum interest at top. In case when the delay is considered, list is sorted in ascending order. In step 3, it checks the nature of the task. The iteration of steps 4 to 17 continues for all MWs. The main objective is that platform selects the MW_i as per offer.

In steps 19 to 29, the scenario for time-sensitive tasks is considered where the decision to bargain or not depends upon time budget $\widetilde{t_i} \leq t_i$ to seek the chances of optimizing platform utility. In all cases, game will not end on agreement when $P_u < 0$. The condition holds as N_{RC_2} would already be assigned by considering P_u. The time complexity for algorithm 1 and algorithm 2 is O(n) as all the operations are performed linearly without involving nested loops. It enhances the capability of the solution in terms of scalability as well.

4. Results

We evaluated the performance of BDM as compared to counterparts by developing a testbed using ASP.net and C#

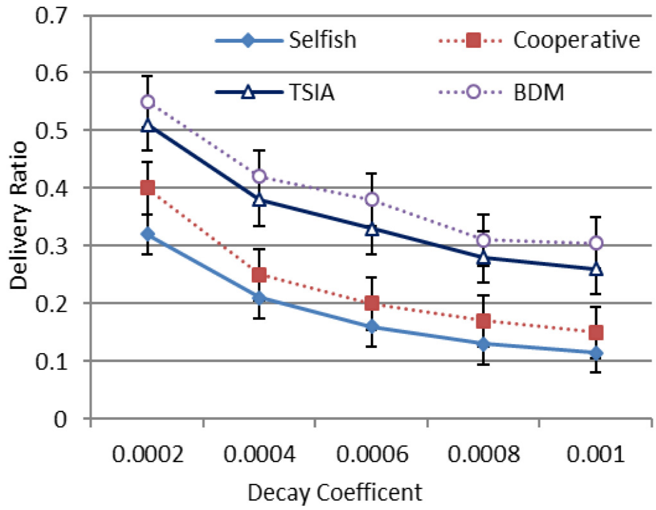

Fig. 2. Effect of decay coefficient on delivery ratio..

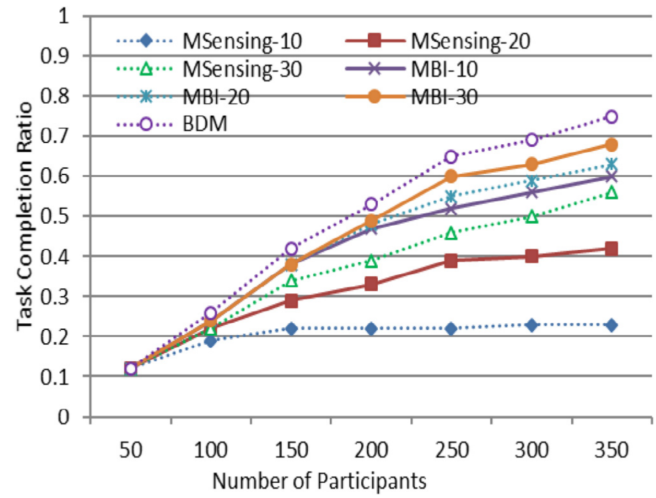

Fig. 3. Task completion ratio for tasks.

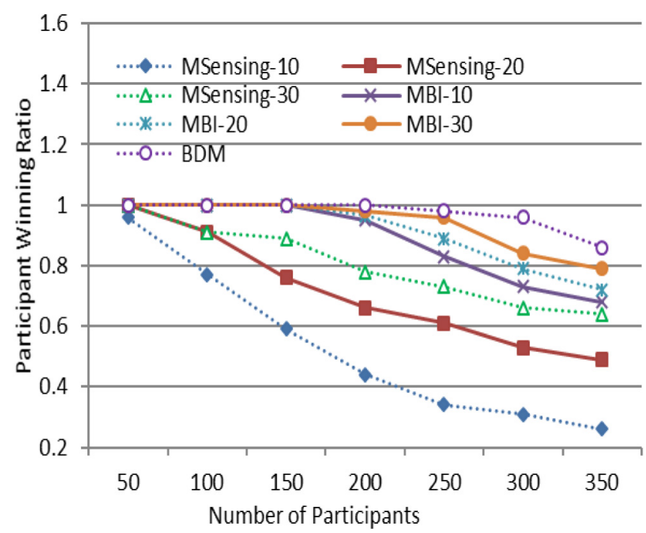

Fig. 4. Participant winning ratio.

where 02 WCF services are deployed on Windows Azure cloud. The BDM and other schemes are implemented as functions in WCF services. A mobile application is also developed using Xamarin and deployed in android and iPhone mobiles used by MWs. The base approaches are MSensing [12], selfish and cooperative scheme, MBI [16] and TSIA [19].

4.1. Decay coefficient

It is a factor that reduces the value of a task over time. Fig. 2 elucidates the decay coefficients and presents the delivery ratio. The increase in decay coefficient has the least effect on BDM for the task delivery ratio because TSIA and other approaches did not consider the movement of MWs. It results in low average credit won by the MWs because the value of task decreases with a large ratio over time.

4.2. Task completion ratio

Fig. 3 illustrates task completion ratio when the number of participants are varied from 50 to 350. It considered standard deviation as σ = [10,20,30]. Results show that MBI-30 is closer to BDM because both of the schemes consider the movement of MW for task completion. The BDM achieves better due to bargaining mechanism. The lowest-performing approach is MSensing because of ignoring the movement of MWs where the tasks in less dense areas remained incomplete. Results show that BDM is about 8% and 27% better in task completion ratio as compared to MBI and MSensing. Fig. 4 elucidates that participant winning ratio is decreased when there are enough number of MWs and platform has more choices/options to select the most appropriate MWs. The BDM outperformed MBI and MSensing by 4% and 24% on average respectively.

4.3. Fraction of task failure

The probability Pr_f of a task left incomplete is $\mathrm{Pr_f} = 1-\binom{\mathrm{T}-1}{\omega-1}/\binom{\mathrm{T}}{\omega} = \frac{\omega}{\mathrm{T}}$ where ω represents the incomplete tasks out of total T tasks announced. Fig. 5 illustrates that probability of task completion failure is 0.00333, 0.0066, 0.01 and 0.0133 when total task failure i = {1, 2, 3, 4} out of total 300 tasks. Similar is the case for MBI and MSensing.

4.4. Social welfare

Due to the trade situation in algorithm 2, the expected platform utility is enhanced along with social welfare by ensuring timely task completion in remote areas. Fig. 6 elucidates that MSensing-10 to 30 improve the social welfare. The MBI-10 to 30 further improve the social welfare by increasing served tasks by involving more MWs. The proposed BDM outperforms by achieving 7% and 22% better social welfare as compared to MBI and MSensing, respectively.

5. Discussions and conclusions

In this work, we proposed a bargaining game based BDM with the intention to increase profitability and social welfare.

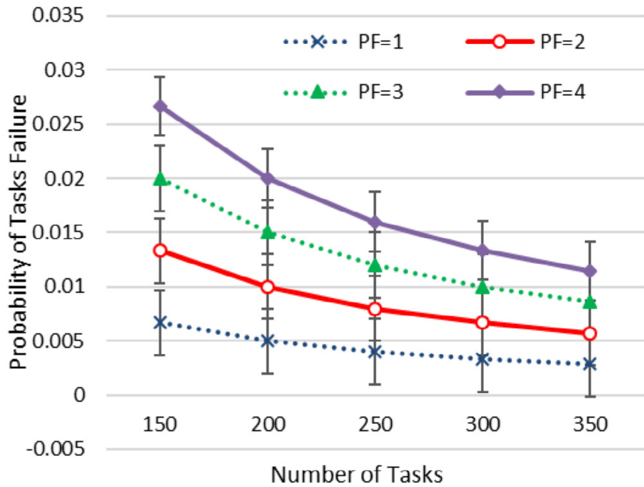

Fig. 5. Probability of task incompletion.

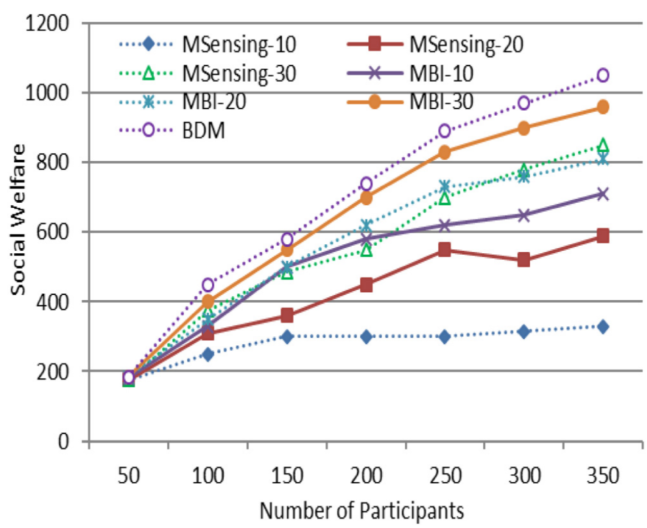

Fig. 6. Social welfare achieved by BDM.

We present two algorithms (i) optimal MWs selection and (ii) optimal bargaining algorithm for rewarding. Algorithm 1 presents the suitable MWs selection to achieve the optimal Nash bar-gaining solution. It utilized the MWs on game thematic model. Algorithm 2 is dedicated to the bargaining game among platform and MW for the transfer of utility when 'agreement' is the decision of the game. We developed a testbed on Windows Azure cloud to validate the results and compare with the counterparts. Results illustrate that BDM outperforms in terms of improving task completion ratio, task winning ratio and social welfare. Results also focus on reducing the fraction of incomplete tasks and decaying co-efficient. BDM improves 8% and 27% task completion ratio, 7% and 22% social welfare in comparison to MBI and MSensing, respectively. In future, we shall consider bargaining with next MWs in the list as well.

Declaration of competing interest

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

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