CrowdDelegate: An MCS-based Approach for Improving Retail Labor Cost-Efficiency

Sherif B. Azmy*, Nizar Zorba†, Hossam S. Hassanein*
* School of Computing, Queen's University, Kingston, Ontario, Canada
† College of Engineering, Qatar University, Doha, Qatar
Emails: sherif.azmy@queensu.ca, nizarz@qu.edu.qa, hossam@cs.queensu.ca

***Abstract*—Following the revolutionary changes the Internet of Things (IoT) has introduced to sensor networks, the Mobile Crowd Sensing (MCS) paradigm aims to utilize people and their smartphones as an extended instrument to sense. However, the benefit of MCS is limited when it comes to microeconomic entities rather than macroeconomic entities. In this paper, we propose CrowdDelegate (CD), an extension of MCS that aims to delegate employee tasks of a consumer hypermarket to customer-workers, utilizing store's loyalty programs interface to recruit participants and reduce operational and logistical costs. This is done by assigning CD tasks to customer-workers present around the store requesting their engagement in a gamified loyalty membership. Customers are rewarded points for the execution of CD activities, allowing the retail business to channel a portion of the loyalty program budget towards the reduction of labor costs. The benefits are two-fold as this approach increases cost-efficiency as well as customer retention. A restricted optimal transport is proposed over the topology of the store to recruit customer-workers based on task costs. This paper sheds light on an unexplored potential of human-centric sensing, extending it to benefit businesses and to engage participants in "doing" instead of only sensing.**

***Index Terms*—crowd-delegation; mobile crowdsensing; internet of things; retail logistics; operations research.**

I. Introduction

Since its inception, the Internet of Things (IoT) encompassed most aspects of human life as every possible device became capable of sensing and communicating. This was followed by the development of Wireless Sensor Networks (WSNs) that pushed IoT dominance to ubiquity. The IoT further expanded to include even humans in the loop in the Mobile Crowd Sensing (MCS) paradigm that exploits people's mobility and their smartphone's sensing capability [1].

MCS aims to utilize people as an extended instrument [2], where administrators prescribe tasks over a designated area of interest, advertise it to participants' smartphones via the MCS server to execute MCS tasks. Participants can accept participatory tasks and actively engage in their implementation, or they can give the permission for the opportunistic harvesting of data on their mobile device when possible. The incentive to successfully complete the task is a reward in the form of a payment or a service. MCS has been found useful in numerous applications in smart city management and operations such as monitoring noise pollution, reporting potholes, air pollution sampling, and others [3].

However, MCS's benefits are limited to macroeconomic entities (relating to a wide-scale, such as a smart city), and participants' actions are limited to only reporting sensed data. While ultimately useful for the large-scale use, entities such as stores, malls, and hypermarkets receive little to no benefit from MCS.

A particular scenario in which MCS could be extended for microeconomic entities is that of customers in a hypermarket. A hypermarket incurs lots of labor cost in the store's display area (or in-store), where shelf stacking and replenishment activities in particular account for 38% to 48% of operational logistical costs. Moreover, 40% of employee time is spent over in-store logistic tasks [4], [5]. Many of these activities do not require a lot of experience and can be delegated to customers. For example, the effort required to perform shelf replenishment could be reduced if the employee's task could be reduced to only transporting the items from the backroom to the aisles, leaving the shelf-stacking part for customer-workers, participants from customer crowd who would perform tasks around a store (For example, the stacking of items according to a planogram that illustrates the shelf stacking plan displayed via an app on their smartphones) [5]. Employing customers as temporary workers via their phones could reduce a significant portion of operational and logistical labor costs.

The use of MCS in scenarios where customers "do" activities that would benefit a business is unprecedented. Thus, we suggest CrowdDelegate (CD), a crowd recruitment scheme based on MCS combined with indoor localization, to delegate a portion of employee's in-store activities to hypermarket customers.

For CrowdDelegate, both the customers and the hypermarket would benefit from reducing operation costs and gaining loyalty points; channeling a portion of operation costs to the budget allocated to loyalty programs. Through the loyalty program's phone app, customers can be further engaged as customer-workers via the gamification of the CD recruitment scheme [6], where doing customer-worker tasks would increase the customer's rank, achievements, ultimately affecting their score; the loyalty points rewarded. This is easily achievable by means of point score multipliers where a customer-worker would earn more points for his dedication; and it would allow allocation of more challenging tasks to customer-workers.

Customers are aiming to minimize their costs by picking items whose prices are discounted or picking cheaper product variants. This customer mentality can act as a natural incentive

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for them to shop. Hypermarkets and retail stores often allocate a portion of their revenue for loyalty programs in an attempt to switch costs; where they would reward customers with points and special offers for their loyalty to their store [7].

In this paper, we discuss the extension of MCS to include the execution of physical tasks to reduce hypermarket operation costs, we prescribe a unique formulation of the optimal transport problem [8] to utilize it as a customer-worker recruiter, and build upon the readily existent loyalty programs to incentivize customers. Furthermore, we devise an operation scheme for a hypermarket to guarantee efficient operation with proper task validation.

The structure of this paper is as follows: Section 2 discusses the notion of MCS delegation and incentivization; Section 3 discusses Optimal Transport as a technique for achieving crowd recruitment and delegation, as well as the integration of application specific costs in the algorithm; Section 4 overviews the simulation of a hypermarket in which customers are recruited; and Section 5 provides a discussion of Crowd Delegation, its importance especially in cost reduction, and open research challenges.

II. Crowd Delegation and Loyalty as an Incentive

Elements of the micro-economy, including hypermarkets, reap little benefit from MCS, where their presence as a stakeholder in MCS is nonexistent. Nonetheless, the private sector can benefit from the approaches developed in MCS by extending the participants' function to delegable tasks.

Hypermarkets have a high customer flow due to the essential nature of the products, as they provide everything from food to furniture. Hypermarkets cater to a large customer population. Groceries, Big Box retail shops including hypermarkets account for 40% of retail foot traffic share [9]. Nevertheless, in-store logistics are costly as the employees have to perform various scheduled activities, with the costliest being shelf-replenishment [5].

Outsourcing these tasks, which do not require a lot of experience, to customers would reduce the effort expected from employees, and thus waste less time in consuming tasks such as stacking items and sorting soon-to-expire products. Nevertheless, this raises concerns regarding task execution quality, the reliability and trustworthiness of customer-workers. Throughout this section, we describe a procedure for customer-worker recruitment, evaluation, quality control of delegated task execution by means of validation tasks as well as propose a simple cost formulation for the delegated tasks.

In MCS, customer incentivization aims to attract potential participants by offering rewards, some of which are tangible such as a monetary payment or a service offered, while some are abstract such as the satisfaction from having provided a service, achieving a public participation rank such as the Google maps local guide program [10], or engaging in a game [11]. In this paper, membership in the loyalty program and status as a customer-worker are incentivized via the loyalty point rewards. This combines the customer's subjective economic rationale behind shopping with the tangible reward of points that can later be redeemed, along the abstract reward of engaging in customer-worker activities as a game.

The benefit of this approach is two-fold: customers will aim to perform the task in order to reduce their checkout costs - by means of points redeemed - and the business will reduce operation costs by delegating employee tasks to customers, by channeling their loyalty program budget into the Crowd Delegation program. Moreover, by introducing a game-like ranking approach, the activity of shopping will be perceived by the customers as an opportunity to invest their time by doing little contributions to the store, which will in turn increase customer retention and loyalty.

A. Hypermarket Crowd Delegation Scheme

CD is different from MCS only in the task execution principle. Tasks are physical activities done in a retail store, a hypermarket. CD is centered around a customer who visits the store to perform their usual shopping activities. If the customer is a member of the store's loyalty program, he/she will be able to collect loyalty points for tasks executed and gain customer-worker rank, with benefits as he/she "level-up". While the customer is shopping, he/she will receive a CD recruitment request that describes the required task. A task such as shelf-stacking would be provided with a planogram (illustrated in Fig. 1), and requested to place items from the trolley on the shelves as per the planogram. Accepting CD tasks is a two-step process in which the customer would accept the task requested via the loyalty application, and that he/she would scan a QR code at the location of the task (i.e., a specific hypermarket aisle).

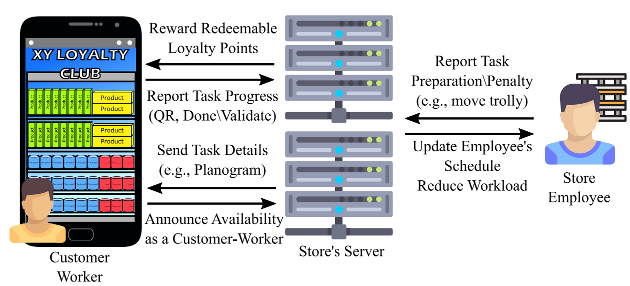

Fig. 1: Customer-Worker Recruitment

Once the task is done, another customer, a validator, who is more experienced (i.e., of a higher customer-worker rank) will be requested to double check the work done by the other customer. Thus, by utilizing more experienced customers who have performed such tasks before, the quality of CD tasks will be guaranteed. If neither the task nor the validation tasks are done, an employee will be requested to perform the task as is his job. If the tasks are successfully performed, both customers will be rewarded. The reward is in the form of loyalty points which can be redeemed as a discount, and in the form of experience towards the next customer-worker rank. The higher a customer's rank the higher the proportion of points earned as they would act as a point multiplier, increasing the flat point reward rate from, for example, 2% of purchases to 2.25%, and multiplying the point reward customer-worker activities by 1.05, giving an extra 5% for the worker's dedication. If a task was not performed correctly, only the validator will be rewarded and the customer worker will receive no points as a penalty and informed of the mistake to correct it next time.

However, the validator might invalidate all other customer-workers in order to keep all the work for themselves. For this reason, a limit should be put on the number of tasks that can be appointed, where no more points would be rewarded. Beyond that limit the customer-worker would have saturated all the rewards collected from performing tasks. This acts as a deterrent to "task hoarding", obliging customer-workers to perform proper validation. Nevertheless, the validator might be in error and wrongly validate a poorly executed task. The employees then, when they are performing routine inventory management tasks would notice this, rectify it, and report it to penalize both the validator and the customer-worker. If no validator was recruited, an employee would then head to the aisle to perform the validation themselves. Ultimately, the CD scheme aims to reduce the effort done by employees while increasing customers' loyalty. This provides a degree of quality control achieved by the customer-workers, resorting to the store's employees when the customer-workers fail penalizing their customer-worker progress, as well as demanding a reliable execution.

We model a task as a triplet $T = \{T_d, T_v, T_{\text{id}}\}$, where $T_d, T_v \in \{0, 0.5\}$ are binary variables that correspond to the task being done and the task being performed correctly or incorrectly reported by the validator, and $T_{\text{id}} \in \mathbb{N}$ denotes the ID of the task being performed, linking to a look-up table corresponding to its reward.

Temporally, the tasks would follow task-cycles. Each epoch, t_{erc}, corresponds to the employee's scheduled shift. If within that epoch the task is performed and validated, the employee does not need to come perform their routine task.

B. Loyalty Points as an Incentive Reward

Before discussing how point rewards are calculated, we shall provide an overview of loyalty programs and the true value of a point. A loyalty point represents *how much a retailer is willing to pay customers as an incentive*, and *how much they want the incentivized behaviour to repeat*. It is often the case that a store's management allocates a percentage, e.g., $1-4\%$, of the revenue as an incentive budget allocated to their loyalty program. Afterwards, a reward rule is determined based on the management's choice of points in return, for example 2% of a specific product's cost is returned in points, which leads to general rule of, for example, 1 point for every one dollar. The points are then rewarded to the customer for their purchase in their loyalty account. The true value of a loyalty point, however, is distributed over various costs as the cost of the reward given to the customer, and the cost of the loyalty program's operation and marketing [12].

However, in the case of CD, the reward rule would reward a number of points per activity (based on T_{id}), and the total number of *activity points* rewarded would be influenced by a point-multiplier that scales with the customer's "loyalty level". That would increase the true value of a loyalty point that goes into a reward by compensating labor costs in it. As a result, less employees would be needed to run a store, and customers would play a pivotal role in reducing the store's labor costs, thus increasing the cost-efficiency of a point.

This approach incorporates the perks of previous MCS approaches in the fact that it incorporates a readily existing loyalty program to incentivize and reward customers for tasks performed in addition to having customers do more than sensing. This allows the schemes of MCS to be utilized to provide more benefit for the store with high demand such as a hypermarket. For this study, we shall assign a task per aisle, and thus a cost per aisle. The cost of the task in aisle (a, b), $C_{a,b}$, over an epoch t_{erc} can the be described as:

$$C_{a,b} = (T_d + T_v)R(T_{\text{id}}) \tag{1}$$

where $R(T_{\text{id}})$ corresponds to the reward value of the task with ID T_{id}, and (a, b) corresponds to the edge describing the aisle, as will be described in Section 3, in which we cover how the store's layout is modeled as a graph.

III. Optimal Transport as a Recruiter

A. Modeling Layout of a Store

For this paper, a store is modeled into a a network in which nodes represent intersections between aisles, edges represents task-laden aisles which have number of CD tasks amounting to a specific cost quantity, to be paid as reward points to the customer-workers. Figure 1 illustrates a sample store layout used in this paper. This graph can then be encoded into a weighted $\eta \times \eta$ adjacency matrix, S:

$$S = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,\eta} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,\eta} \\ \vdots & \vdots & \ddots & \vdots \\ s_{\eta,1} & s_{\eta,2} & \cdots & s_{\eta,\eta} \end{bmatrix} \tag{2}$$

where η corresponds to the size of the graph's vertex set, and the weights $s_{a,b}$ correspond to the weight of the edges between vertex a and vertex b. In this case, for the optimal transport, both the vertices and the edges are weighted. The vertices are weighted by the number of participants in the surrounding edges and the edges are weighted by the net point cost of the tasks to be performed in them, which is based over the cost function described in Eq. (1). This model will allow the usage of Optimal Transport as an optimal, yet flexible, recruitment algorithm.

B. Overview of Optimal Transport

The Optimal Transport problem aims to find the cheapest transport plan to transport between two probability distributions $(\boldsymbol{\alpha}, \boldsymbol{\beta})$ such that the transportation cost of each element in $\boldsymbol{\alpha}$ to $\boldsymbol{\beta}$ is the lowest possible [8]. The distributions can be described as:

$$\boldsymbol{\alpha} = \textstyle\sum_{k=1}^{N_\alpha} \alpha_k \delta_{x_k}, \quad \boldsymbol{\beta} = \textstyle\sum_{l=1}^{N_\beta} \alpha_l \delta_{y_l} \tag{3}$$

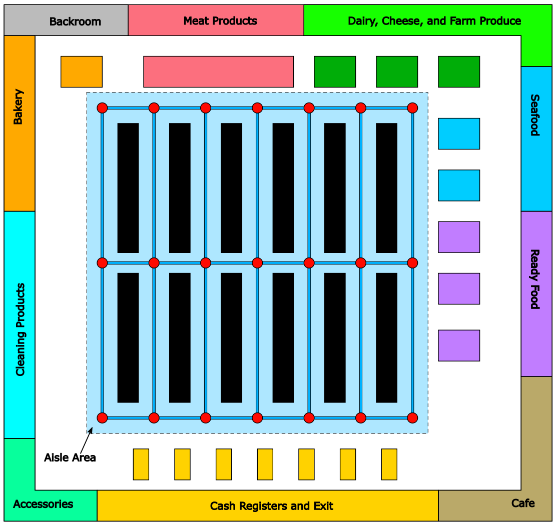

Fig. 2: Sample store layout, where red nodes are aisle intersections and participant recruitment points; blue edges represent aisles in which participants execute their CD tasks.

where α_k, β_l correspond to masses located at x_k, y_l, respectively, and $\delta_{x_k}, \delta_{y_l}$ correspond to the dirac deltas positioned at x_k, y_l, respectively.

A function $c(x_k, y_l)$ prescribes the mappings of $\alpha \in \boldsymbol{\alpha}$ and $\beta \in \boldsymbol{\beta}$ to values that represent the cost of the transport between these two masses. The costs are collected in a matrix $\mathbf{C}$ where $C_{kl} = c(x_k, y_l) \in \mathbb{R}^{N_\alpha \times N_\beta}$. It is often the case that the cost is defined as the L^2 distance where $c(x_k, y_l) = \|x_k - y_l\|^2$.

The best transport plan, $\mathbf{P}^\star$ is a choice that is selected from a set of admissible couplings $\mathbf{U}(\boldsymbol{\alpha}, \boldsymbol{\beta})$, in which all permutations of couplings, $\mathbf{P} \in \mathbb{R}_+^{N_\alpha \times N_\beta}$, are contained. That choice of $\mathbf{P}^\star$ ensures that the average cost is minimal. For the matrix $\mathbf{P}$, the sum of the columns would yield the vector $\boldsymbol{\alpha}$, and the sum over the columns would yield the vector $\boldsymbol{\beta}$, while each element $\mathbf{P}_{kl}$ describes the amount of mass transferable between each mass α_k and its corresponding math β_l, under the Monge-Kantorovich formulation that allows the splitting of the masses. The problem can be described using mathematical optimization notation as:

$$\begin{array}{ll} \text{minimize} & \langle \mathbf{C}, \mathbf{P} \rangle \\ \text{subject to} & \mathbf{P} \in \mathbf{U}(\boldsymbol{\alpha}, \boldsymbol{\beta}) \end{array} \tag{4}$$

where $\langle \mathbf{C}, \mathbf{P} \rangle = \sum_{kl} \mathbf{C}_{kl} \mathbf{P}_{kl}$.

Linear programming was found to be a feasible method for obtaining a solution for optimal transport problems [8]. The problem can be cast in the standard form of linear programming as:

$$\begin{array}{ll} \text{minimize} & \mathbf{c}^T \mathbf{P} \\ \text{subject to} & \mathbf{p} \in \mathbb{R}^{n_\alpha n_\beta} \\ & \mathbf{A}\mathbf{p} = \left[\begin{smallmatrix} \boldsymbol{\alpha} \\ \boldsymbol{\beta} \end{smallmatrix}\right] \end{array} \tag{5}$$

where $\mathbf{c}$ is a flattened formulation of the matrix $\mathbf{C}$, $\mathbf{p}$ is the flattened form of matrix $\mathbf{P}$, and the matrix $\mathbf{A}$ is defined as:

$$\mathbf{A} = \begin{bmatrix} \mathbb{1}_{N_\alpha}^T \otimes \mathbb{I}_{N_\beta} \\ \mathbb{I}_{N_\alpha} \otimes \mathbb{1}_{N_\beta}^T \end{bmatrix} \in \mathbb{R}^{(N_\alpha + N_\beta) \times N_\alpha N_\beta} \tag{6}$$

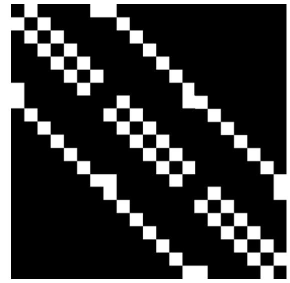

Fig. 3: Set of Admissible Couplings $\mathbf{U}^\star(\boldsymbol{\alpha}, \boldsymbol{\beta})$, also models the adjacency matrix of the store's layout. White squares represent "legal" transports, while black squares represent "illegal" or undesired transports.

where $\mathbb{1}_L$ is the indicator vector of length L, and $\mathbb{I}_L$ is the identity matrix of size $L \times L$.

The constraint $\mathbf{P} \in \mathbf{U}(\boldsymbol{\alpha}, \boldsymbol{\beta}) \leftrightarrow \mathbf{A}\mathbf{p} = \left[\begin{smallmatrix} \boldsymbol{\alpha} \\ \boldsymbol{\beta} \end{smallmatrix}\right]$ requires that for a coupling $\mathbf{P}$ to be admissible for the linear program, the sum over its rows and columns should yield $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$, respectively. Furthermore, the sum masses of $\boldsymbol{\alpha}$ is equal to the sum of masses of $\boldsymbol{\beta}$, summing up to 1. However, the constraints of the linear program can be modified to incorporate the geometry of the store. By limiting the sum over the whole row to a specific set of "legal" couplings (or transports), the optimal transport can be "restricted" to yield solutions that respect the store's layout geometry. Fig. 3 illustrates the admissible couplings (legal transports) for the layout provided in Fig. 2. Values in black and white represent inadmissible and admissible couplings, respectively. Thus, the matrix $\mathbf{A}$ can be updated by updating the lower half to n_α horizontally concatenated $n_\alpha \times n_\beta$ matrices, each containing a single row of 3, as per the store's administrator's needs. The feasibility of the solution, as a result, is reliant on the choice of $\boldsymbol{\beta}$ as well as the cost matrix. Algorithm 1 describes the procedure for customer-worker recruitment.

Algorithm 1 Algorithm for CrowdDelegate Customer-Worker Recruitment

Input: $\mathbf{C}, \boldsymbol{\alpha}, \boldsymbol{\beta}, N_{\text{total}}, \mathbf{U}^\star(\boldsymbol{\alpha}, \boldsymbol{\beta})$
Output: $\mathbf{P}^\star$

$\mathbf{C}_{\text{CD}} \leftarrow \{\mathbf{C}_{\text{CD},kl} : \mathbf{C}_{\text{CD},kl} = [R(T_{\text{id}})]_{kl}\}$
$\mathbf{c} \leftarrow \texttt{flat}(\mathbf{C}_{\text{CD}})$
$\mathbf{p} \leftarrow \texttt{flat}(\mathbf{P})$
Compute $\mathbf{A}$ (Fig. 3)
Solve Linear Program for
    $\mathbf{p}^\star = \texttt{min}\ \mathbf{c}^T\mathbf{p}\texttt{:}\ A\mathbf{p} = [\boldsymbol{\alpha}; \boldsymbol{\beta}]$, $\mathbf{p} >= 0$
$\mathbf{P}^\star = \texttt{reshape}(\mathbf{p}^\star)$
return $\mathbf{P}^\star$

This allows the administrator to control how customer-workers are transported through the shop if they seek to ensure a specific path for each. Consequently, the cost matrix will follow the form of Fig. 3, encouraging the assignment of costs to legal couplings. However, this could be limiting for the extent of transportation of customer workers, limiting them to only a single level of depth throughout the store's

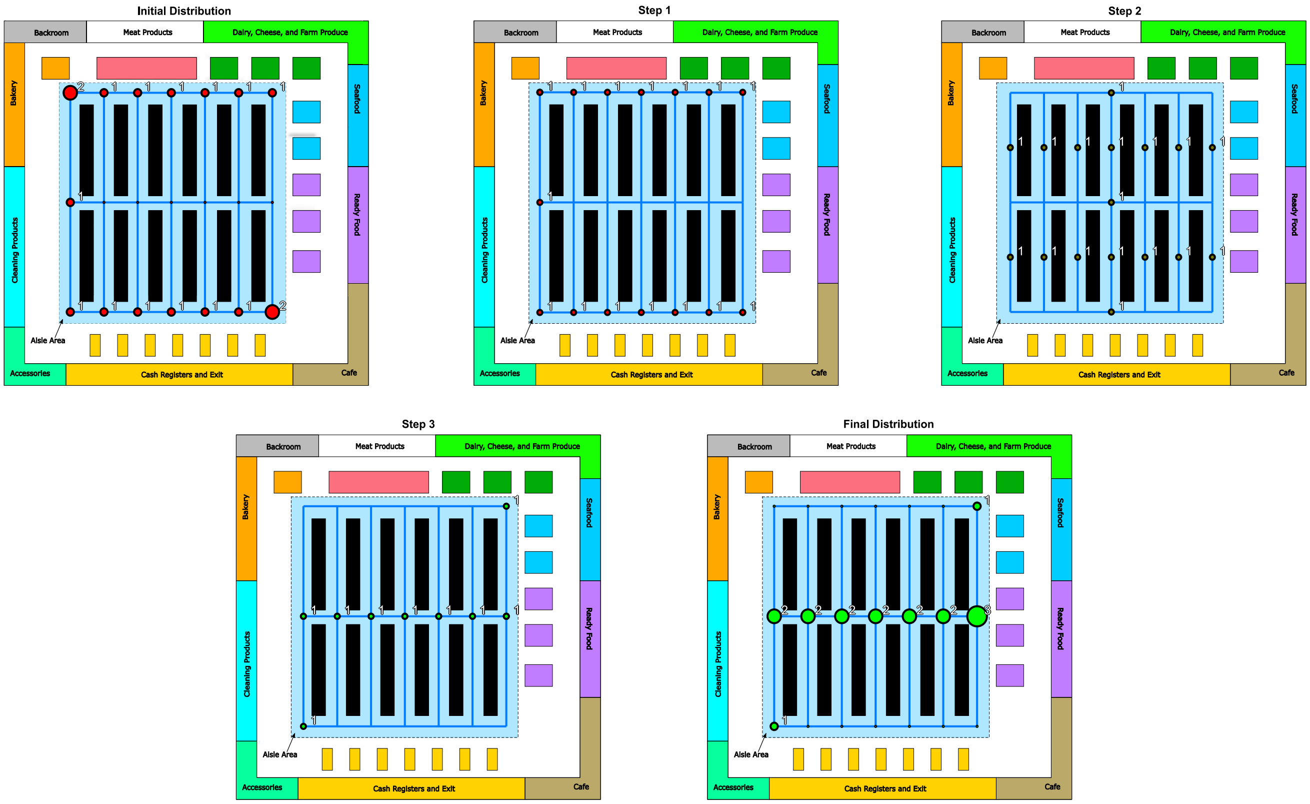

Fig. 4: Simulation of the optimal transport of MCS participants

network to prevent moving from one side of the store to another. Moreover, for the duration of a sensing cycle, the administrator will be capable of recruiting customer-workers in an opportunistic manner, when their location coincides with one that requires a participatory CD task to be done.

IV. Computer Simulation

To test the proposed algorithm over MATLAB, we generated the costs for the tasks, $R(T_{\text{id}}) \in \mathcal{U}(2, 5)$ into the cost matrix $\mathbf{C}$, following the coupling constraints of $\mathbf{U}(\boldsymbol{\alpha}, \boldsymbol{\beta})$. The results are presented in Fig. 4. The colors of the circles represent the time elapsed between the initial and the final post-recruitment distributions of customer-workers, and the labels represent the number of participants in a certain node or across a certain edge. Over a portion of the duration of a sensing cycle, the system seeks to recruit a number of customer-workers from the nodes in the "Initial Distribution". Based on the admissible couplings presented in Fig. 3, the customer-workers are recruited and requested to perform tasks over their corresponding aisles. The upper left and lower right corners seek to recruit two customer-workers each: one for the aisle in the vertical direction, and one for the aisle heads in the horizontal direction. In "Step 1" the participants, represented as masses, engage in their tasks, splitting towards their respective tasks. Steps 2-3 illustrate the possibility of assigning more than a task per customer-worker, providing, for example, stacking planograms on the fly. Finally, the customer-workers finish their tasks. The same algorithm could be used for task validation for completed tasks.

V. Conclusion

The IoT paradigm based on sensors and WSNs, such as MCS provide a rich field that extended IoT from things to people, integrating their ability to sense via their mobile phones and their opinions in the data assimilation process. Various frameworks and techniques were developed to address MCS concerns of incentivization, trustworthiness, reputation, and quality. The benefits of these frameworks are not limited to sensing, they can be extended to engage participants more and employ them to do certain activities.

In this paper, we have proposed CrowdDelegate, a scheme that seeks to extend the MCS framework from the wide-scale of macroeconomic entities, such as a smart-city, to the local scale of microeconomic entities, particularly hypermarkets. The proposed scheme combines the customer's need to shop for groceries with the hypermarket's need of retaining customers and desire to maximize revenue. This is illustrated in the extension of loyalty programs to act as an interface to CD systems, in order to channel operational and logistical labor costs from employees to customer-workers, increasing the effectiveness of the loyalty program's budget. A description of the customer-worker recruitment and task-execution procedures is described in which customer-workers are double checked by peers, then rewarded or penalized via a gamified ranking of customer-worker progress. This requires participants to maintain a level of reliability to earn the perks of the CrowdDelegate program while ensuring task execution quality by peer customer-workers acting as validators. A restricted version of the optimal transport problem was presented to opportunistically recruit participants throughout the store for the participatory execution of the tasks, of which a computer simulation was provided.

The notions conceived in this paper aim at an unexplored potential of using people in a way that benefits both business and customer by empowering the bond between them via the gamification of the customer's experience and the reduction of the cost of doing business.

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