Queuing Algorithm for Effective Target Coverage in Mobile Crowd Sensing

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***Abstract*—In recent years, various researches have been conducted in order to find ways to cover a target or groups of targets with priority-based target coverage and sensor deployment mechanisms taking the front seats. However, with these researches, effective target coverage has been a recurrent issue due to various factors like conflict between sensors and excessive waiting time for targets to be covered. In this paper, we proposed an algorithm based on queuing theory in tandem with mobile crowd sensing to tackle these issues. To do this, first, we develop some models which are based on the birth-and-death mechanism (one of the tools in queuing theory) to determine how long a target has to wait, the mean busy period of sensors and mean idle period of sensors. While developing these models, we consider cases where there exist a single sensor and n-sensors in the system. Based on these models, we develop the required algorithm. The simulation result shows that as the number of sensors increases relative to the number of targets, an average time before a target gets discovered is 0.2 s and sensor utilization decreasing toward zero as the number of sensors increases.**

***Index Terms*—Birth and death mechanism, mobile crowd sensing (MCS), queuing theory, sensor utilization, sensors.**

Fig. 1. Simple MCS illustration.

I. Introduction

Mobile crowd sensing (MCS) involves the use of crowd together with the sensing capabilities of various mobile devices, such as smartphones or wearable devices to cover a target for onward inference [1]–[3]. See Fig. 1 for a simple illustration. The first part denotes sensors moving into the target area and collecting the required data. The data is then sent to the data center for processing and inference. For a specific example, suppose for proper city planning, the city managers want to get information about an area/areas full of illegal markets in order to curb them. They could use information from vehicles that ply that route. In this case, the vehicles are the sensors, while the area where the market is located is the target. The information gathered can either be saved in the cloud or sent to the information hub for onward processing and feedback (see Fig. 2).

Based on the crucial need for MCS which includes but not limited to, the above example, environmental monitoring, flood detection, and military applications [4]–[6], there have been calls for effective target coverage as this will give a meaningful result and help in quality decision making.

Effective target coverage has been a hot research topic in recent years. Coverage concept is a measure of the quality of service of the sensing function and is subject to a wide range of interpretations due to a large variety of sensors and applications [7], [8]. The reason is that many factors come into play when a sensor or group of sensors are monitoring a target. These factors have direct and indirect effects on these sensors and their coverage results. Since the goal of target coverage has always been the effective monitoring of all targets in an area, achieving this goal is sometimes a herculean task and thus, when it is achieved, it is either late or ineffective. This failure can be attributed to the fact that early sensing devices are bulky, consume lots of energy and maybe affected

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Fig. 2. Target coverage for city planning.

by environmental factors. These factors led to improvement in the production of effective sensing devices and attendant components. One of such improvements is the embedding of major sensors in smart devices, mobile phones or other personalized devices that are uniquely identifiable and are equipped with communication interfaces.

Recent advances in smartphone manufacturing have led to heavy upgrades in terms of capabilities [9], [10] and durability in these devices. With these smart devices, sensor coverage has introduced some level of improvement through various methods that aim at effective coverage [11]. However, these improved methods also have their drawbacks as highlighted below.

1) *User Mobility*: Smart devices are owned and carried by people. People move toward destinations that are mostly not intended to be monitored.
2) *Power Limitation*: A smart device may not be effectively powered for sensing to be carried out.
3) *Network Coverage*: For proper sensing to be carried out, the output has to be relayed in real time as such smart devices have to be connected to a backhaul network. Now, if there is a network failure, sensing result may not be immediately transmitted and could affect the purpose of sensing.
4) *Clashes*: A single target can be sensed by multiple sensors, and this phenomenon may lead to clashes. Clashes in this case, denote the situation where multiple sensors cover the same target and interfere with each other. Indeed, this may result in wasted resources.

In order to provide solutions to these drawbacks, we intend to use queue theory in modeling the target coverage.

Queuing theory involves the mathematical study of queues or waiting lines [12], [13]. Waiting lines are the phenomena that occur whenever the current demand for a service exceeds the current capacity to provide that service. Decisions regarding the capacity to provide services must be made frequently. These decisions can be linked to target coverage results. In this case, we can consider the targets to be covered as the customers in the queue system and the sensors as the servers. An effective target coverage could lead to remarkable broader and societal impacts.

In doing this, we intend to model the entire coverage system as a birth-and-death mechanism. In which case, the arrival of a sensor signifies a birth process and the exit after target coverage signifies a death process. This mechanism creates room for efficient coverage monitoring and easy flow.

Based on the introductory statements, this paper intends to contribute to the MCS literature with the following points.

1) Create models using queue theory techniques to provide answers to the following questions. How long should a target wait before it is covered? What is the mean busy period of sensors? and What is the mean idle period of sensors?
2) Create an algorithm based on: a) the models derived in 1) above and b) the birth-and-death mechanism for easy flow of target monitoring in crowd sensing. The algorithm starts off with the arrival of sensors, then computation of parameters and ends with the assigning of sensors to targets.

The rest of this paper is organized as follows. Section II presents a brief literature review. In Section III, we build the required models and propose the algorithm for target coverage. In Section IV, evaluation is conducted to test out the algorithm while Section V concludes this paper and discusses future work.

II. Literature Review

Diverse research efforts have been carried out in a bid to effectively cover targets maximally. In this section, we discuss some of the works done in this regard.

This paper in [14] addressed the problem of detecting and describing traffic anomalies using crowd sensing with two forms of data: 1) human mobility and 2) social media. The existing traffic-anomaly detection methods were used to identify anomalies according to drivers' routing behavior on an urban road network. They represented this using a road network where individuals' routing behaviors significantly differ from their original patterns. However, data from social media are in most cases unreliable due to the fact that people in most cases falsify their true positions on social media. This can lead to a wrong coverage result.

For time consciousness, this paper in [15] proposed an online scheduling problem which determines sensing decisions for smartphones that are distributed over different regions of interest by proposing a centralized online scheduling algorithm based on stochastic optimal control and a distributed online scheduling algorithm based on distributed correlated scheduling. The objective of this paper was improving data utility. It however fails to account for what happens if there are power failures during coverage, neither do they incorporate the power consumption threshold.

This paper in [16] proposed an on-demand scheduling algorithm in order to maximize covering utility. This method involved three approaches that are combined with queuing models to solve the scheduling mobile charger problem.

But there is no set parameter or solution provided should the chargers suddenly become unavailable. This setback might have adverse effect on proper target coverage.

In order to cope with the energy crisis, this paper in [17] designed efficient sensor duty cycles to ensure that respective targets are covered sufficiently while the inactive sensors are put to sleep. To achieve this, the authors developed two models and also presented a time slot allocation scheme for each sensor. However, approximation algorithms might not generally give an exact time when a sensor should go off or monitor a target. The implication of this is, if a sensor goes to sleep at the wrong time, a target might be left stranded.

Li *et al.* [18] deployed a network along 1-D line using a Poisson distribution and analyzed the expected k-coverage proportion, full k-coverage probability, and partial k-coverage probability. While doing this, the authors developed mathematical models using queue theory to describe the relationships between the node densities. This, however, is limited due to its 1-D nature.

Solmaz *et al.* [19] proposed a model for human mobility in theme parks. The authors combined the nondeterministic nature of movement decision with deterministic behavior of attractions using mobile devices along with queuing models. The results showed a better match to the real world data when compared to other movement models. But building a model based on categorized human movements might hamper proper target coverage. Because if a person decides to change his base due to a change in plan, then the target that is supposed to be covered might not get covered.

Hu *et al.* [20] developed an application called SmartRoad, a crowd-sourced road sensing system that detects and identifies traffic regulators and traffic lights. SmartRoad works on sensing data collected from GPS sensors from in-vehicle smartphones. It blends to different application scenarios by choosing the most appropriate information representation and transmission schemes while evolving its core detection and identification engines to effectively take advantage of any external information. However, choosing target arbitrarily without setting priorities reduces the efficiency of target coverage. Moreso, restricting the data acquisition to vehicle resident smartphones makes data acquisition sidelined. We might want to monitor targets that are not assessible by road but can be reached by walking. As such this method may not fit all purposes.

In order to stay within the budget limitation of crowd sensing incentives, Jaimes *et al.* [21] proposed an incentive assignment mechanism for crowd sensing which meets the goal of maximizing coverage of the area of interest, while at the same time staying within a budget constraint. The algorithm takes into account the area covered by the participants' sensors and the spread of these sensors through a target area. This allows more representative sampling. Furthermore, there have been recent studies where user incentives that guarantee staying within the budget limit have been integrated with trustworthiness assurance in order to improve the usefulness of the crowd sensed data [22]–[24]. This paper, however, intends to develop certain required parameters so that data integrity will not be hampered by budget constrains.

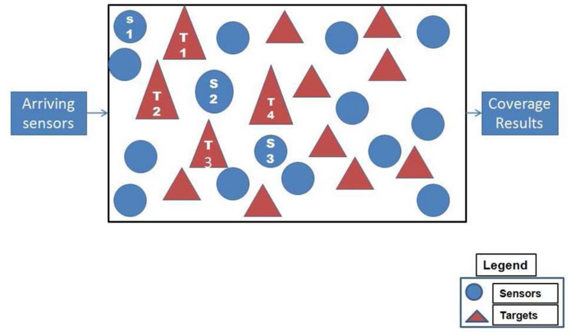

Fig. 3. Target coverage depiction in MCS.

Based on the related work, it can be stated that MCS calls for an effective solution for building a scheduling platform for the sensors whose target areas overlap. Hence, the motivation behind this paper is to address these open issues–to the best of our knowledge–for the first time in the literature.

III. Model Building and Algorithm

This section involves the development of the model and algorithm. However, before we begin building the required model, it is worthwhile stating the problem, defining some basic required items and describing certain processes.

A. Problem Statement

Suppose the MCS platform has identified a number of targets that need to be covered by deployed sensors, i.e., built-in sensors in smart devices. We intend to distribute these sensors in such a way that they cover these targets subject to certain constraints. As seen in Fig. 3, we want to develop an algorithm such that $S1$ can cover $T1$ and $T2$, while $S2$ can cover $T4$, etc. Furthermore, we intend to incorporate the following.

1) Include certain steps to ensure that no two sensors monitor same target at the same time.
2) If a sensor is not in use, it should enter the sleep mode.
3) If a mobile device is low in power, it can automatically pass target coverage to the next available mobile device within its coverage vicinity.

It should be noted that one sensor can indeed monitor more than one target. However, to proceed further, we would like to make some basic definitions.

1) *Input Source:* Input source is the source of the sensors, which in this case, is the smart device. The population from which the input source is derived from is called the calling population.

   Assumption 1: The crowd sensing population is assumed to be unlimited. For mathematical convenience and without loss of generality, we assumed that the crowd sensing population is infinite, however, we understand that over a large period of time, the population could be a relatively large finite number.

   Assumption 2: The probability distribution of the time between consecutive arrivals of users follows a negative exponential distribution.

2) *Queuing Discipline:* This refers to the order in which members of the queue are selected.
3) *Service Mechanism:* The service mechanism consists of one or more service facilities (service environments) each of which contains one or more servers [25]. If there exists more than one environments, the customer may receive service from a series of servers.
4) *Service Rate:* Service rate denotes the elapsed time from the commencement of monitoring to its completion for a target.

B. Queuing Process

This involves the process in which a customer is served by a server [26]. In other words, the process in which a sensor covers or monitors a target.

The server needs not be a single smart device; it may be a group of smart devices. In the same vein, the targets are always more than one. Furthermore, it is not necessary for there to be a physical line forming in front of a physical structure that constitutes the service facility. That is, members of the queue may be scattered throughout an area waiting for a server or group of servers [26]. As such, a sensor or a group of sensors assigned to a given area constitutes the service facility for that area.

At the initial stage, the coverage area will be affected by the initial state and by the time that has elapsed, the system is said to be in a transient condition [27]. After sufficient time has elapsed, the state of the system becomes essentially independent of the initial state and elapsed time. At this point, the system can be considered to have reached a steady state condition where the probability distribution of the coverage area remains the same over time [28], [29].

The system is said to be overloaded if the traffic intensity (ρ) exceeds one. An overload situation stands for the case where the number of clients is greater than the number of servers. Let $\chi(A)$ denotes the characteristic function (expected value) of event A, as presented

$$\chi(A) = \begin{cases} 1, & \text{if } A \text{ occurs} \\ 0, & \text{if } A \text{ does not occur} \end{cases} \tag{1}$$

and $N(t) = 0$ denotes the event at time T. If the sensor is idle, then the utilization of the sensor during time T is formulated as

$$\frac{1}{T}\int_0^T \chi\big[N(t) \neq 0\big]dt \tag{2}$$

where T is a time point.

As $T \to \infty$, we get the utilization of the sensor denoted by U_s and the following relations hold with a probability of one as shown:

$$U_s = \lim_{T\to\infty} \frac{1}{T}\int_0^T \chi\big[N(t) \neq 0\big]dt = 1 - P_0 = \frac{E\sigma}{E\sigma + E_i}. \tag{3}$$

In (3), P_0 is the steady state probability that the sensor is idle, $E\sigma$ and E_i denote the mean busy period and mean idle period of the sensors, respectively.

In an m sensors system, the mean number of arrivals of a given sensor during time T is $\lambda T/m$ given that the arrivals are uniformly distributed over the sensors. Thus, the utilization of a given sensor is

$$U_s = \frac{\lambda}{m\mu}. \tag{4}$$

Another important measure of the system is the throughput (TP) of the system. TP is defined as the mean number of requests serviced during a time unit. In an m sensor system, the mean number of completed services is $m\rho\mu$ and the TP is formulated as shown

$$\mathrm{TP} = mU_s\mu. \tag{5}$$

Let us suppose W_j and T_j are the waiting and response time of the jth target, respectively, the response time, T_j can be formulated as in (6) where S_j denotes the service time

$$T_j = W_j + S_j. \tag{6}$$

C. Model Building: The Birth-and-Death Mechanism

According to this model, every sensor arrival and departure into the system occur according to the birth and death process. That is, the arrival of a new user into the system is referred to as birth, while the departure of user that has been served is called death. The birth and death mechanism suggests that individual births and deaths occur randomly where their mean occurrence rates depend only upon the current state of the system. Based on this, the following assumptions are made.

Assumption 3: Given $N(t) = n$, the current probability distribution of the remaining time until a new target is discovered is exponential with parameter $\lambda_n (n = 0, 1, 2, \ldots)$.

Assumption 4: Given $N(t) = n$, the current probability distribution of the remaining time until the next death (service completion) is exponential with parameter $\mu_n (n = 0, 1, 2, \ldots)$.

Based on these assumptions, the steady state distribution for the birth–death process is formulated as

$$P_i = \frac{\lambda_0 \cdots \lambda_{i-1}}{\mu_1 \cdots \mu_i} P_0, \quad i = 1, 2, \ldots \tag{7}$$

P_i in (7) are the steady state probabilities for $i = 1, 2, \ldots$ and P_0 is the steady state probability if a sensor is idle. Thus,

$$P_0^{-1} = 1 + \sum_{i=1}^{\infty} \frac{\lambda_0 \cdots \lambda_{i-1}}{\mu_1 \cdots \mu_i}. \tag{8}$$

Let N_a and N_d denote the state of the process at the instant of births and deaths, respectively. Also, let $\prod_k = P(N_a = k)$ and $D_k = P(N_k = k)$ $k = 0, 1, 2, \ldots$ denote the distributions of N_a and N_d, respectively, then applying Bayes's theorem, we have

$$\prod_k = \lim_{h\to 0} \frac{(\lambda_k h + \phi(h))P_k}{\sum_{j=1}^{\infty}\big(\lambda_j h + \phi(h)\big)P_j} = \frac{\lambda_k P_k}{\sum_{j=0}^{\infty} \lambda_j P_j}. \tag{9}$$

Similarly

$$D_k = \lim_{h\to 0} \frac{(\mu_{k+1} h + \phi(h))P_{k+1}}{\sum_{j=1}^{\infty}\big(\mu_j h + \phi(h)\big)P_j} = \frac{\mu_{k+1} P_{k+1}}{\sum_{j=0}^{\infty} \mu_j P_j} \tag{10}$$

and $\phi(h)$ is an estimate due to the property of the poisson process.

Since, $P_{k+1} = (\lambda_k/\mu_{k+1})P_k$, $k = 0, 1, 2, \ldots,$ thus

$$D_k = \frac{\lambda_k P_k}{\sum_{i=0}^{\infty} \lambda_i P_i} = \prod_k . \tag{11}$$

Equation (11) implies that for any state of the system k, the mean discovery rate is equal to the mean leaving rate. This is called the balance equation. Generally, we assume that a customer is served by one server at a time. That is, a target is covered by a sensor at any point in time. This gives us a queue model of the form $M/M/1$.

If $N(t)$ denotes the number of targets in the system at time t, it can be said that the system is at state k if $N(t) = k$. Consequently, $N(t)$ is a continuous time Markov chain with state space $\{0, 1, \ldots, \}$. As such $N(t)$ is a birth–death process with rates, $\lambda_k = \lambda$; $k = 0, 1, 2, \ldots$ and $\mu_k = \mu$; $k = 1, 2, 3, \ldots$ That is, all the birth rates are denoted by λ whereas all the death rates are denoted by μ.

To get the steady state distribution, we substitute these rates into (7), which in turn, leads to

$$P_k = P_0 \prod_{i=0}^{k-1} \frac{\lambda}{\mu} = P_0 \left(\frac{\lambda}{\mu}\right)^k, \quad k \geq 0 \tag{12}$$

and using the normalization condition, we have

$$P_0 = \left(1 + \sum_{k=1}^{\infty} \left(\frac{\lambda}{\mu}\right)^k\right)^{-1} = 1 - \frac{\lambda}{\mu} = 1 - \rho \tag{13}$$

where $\rho = (\lambda/\mu)$. Thus,

$$P_k = (1-\rho)\rho^k. \tag{14}$$

Equation (13) is a modified geometric distribution with success parameter $1 - \rho$.

When the mean number of targets in the system, are calculated, (15) is to be formulated

$$\begin{aligned} \bar{N} &= \sum_{k=0}^{\infty} kP_k \\ &= (1-\rho)\rho \sum_{k=1}^{\infty} k\rho^{k-1} \\ &= (1-\rho)\rho \sum_{k=1}^{\infty} \frac{d\rho^k}{d\rho} \\ &= (1-\rho)\rho \frac{d}{d\rho}\left(\frac{1}{1-\rho}\right) \\ &= \frac{\rho}{1-\rho}. \end{aligned} \tag{15}$$

In addition, the mean number of targets waiting to be covered and sensor utilization are formulated as in (16) and (17), respectively

$$\begin{aligned} \bar{Q} &= \sum_{k=1}^{\infty} (k-1)P_k \\ &= \sum_{k=1}^{\infty} kP_k - \sum_{k=1}^{\infty} P_k \\ &= \bar{N} - (1 - P_0) \\ &= \bar{N} - \rho \\ &= \frac{\rho^2}{1-\rho} \end{aligned} \tag{16}$$

$$\begin{aligned} U_s &= 1 - P_0 \\ &= \frac{\lambda}{\mu} \\ &= \rho. \end{aligned} \tag{17}$$

TABLE I
BASIC NOTATIONS

$N(t)$	Number of targets in the queuing system at time t
s	Number of servers (sensors) in queuing system
λ_n	Discovery rate of a new target
μ_n	Mean service rate for overall system
$\bar{Q}$	Mean queue length
$\bar{n}$	Mean number of busy sensors
$\bar{N}$	Mean number of targets in the system
$\bar{W}$	Mean waiting time
$\bar{T}$	Mean response time
U_s	Sensor utilization
$E\delta_r$	Mean busy period
P_0	Steady state probability
$\prod_k$	Distribution of births
D_k	Distribution of deaths
ρ	Traffic intensity

Suppose $1/\lambda$ is the mean idle time of the sensor and $E\delta$ is the mean busy period of the sensor, then the steady state probability can be represented as

$$P_0 = \frac{\frac{1}{\lambda}}{\frac{1}{\lambda} + E\delta}. \tag{18}$$

Combining (17) and (18), we obtain

$$E\delta = \frac{1}{\lambda}\frac{\rho}{1-\rho} = \frac{1}{\lambda}\bar{N} = \frac{1}{\mu - \lambda}. \tag{19}$$

Equations (8), (9), (14)–(16), and (18) are the required models in the presence of a single sensor in the system. Table I shows a summary of the basic notations.

In the next section, we consider the case where we have multiple sensors in the system.

D. n-Sensor Case

Suppose, we have a case where there are random arrivals of sensors. That is, the trajectories of mobile users are not specific, they arrive randomly at a particular area and the targets get monitored, and each sensor is operating independently of each other.

Let X_i be exponentially distributed random variables with parameter μ_i, $(i = 1, 2, \ldots, r)$ and let Y denotes their minimum, then Y is exponentially distributed with parameter $\sum_{i=1}^{r} \mu_i$. In this case, the probability of having the minimum of these random variables less than a certain value, x, can be formulated by (20). The equation can be generalized as

$$P(Y < x) = 1 - P(Y \geq x) = 1 - P(X_i \geq x, i = 1, \dots, r) \tag{20}$$

$$P(Y < x) = 1 - \prod_{i=1}^{r} P(X_i \geq x) = 1 - e^{-(\sum_{i=1}^{r})x}. \tag{21}$$

With this, the number of targets in the system demonstrate a birth–death process with the following transition probabilities:

$$P_{k,k-1}(h) = \mu_k h + o(h) \tag{22}$$

$$P_{k,k+1}(h) = \lambda h + o(h) \tag{23}$$

where

$$\mu_k = \min(k\mu, n\mu) = \begin{cases} k\mu, & \text{for } 0 \leq k \leq n \\ n\mu, & \text{for } n < k. \end{cases} \tag{24}$$

and the stability condition $(\lambda/n\mu) < 1$.

To get the distribution P_k, we consider two scenarios according to how μ_k depends on k.

1) If $k < n$, in (25) is used

$$P_k = P_0 \prod_{i=0}^{k-1} \frac{\lambda}{(i+1)\mu} = P_0 \left(\frac{\lambda}{\mu}\right)^k \frac{1}{k!}. \tag{25}$$

2) If $k \geq n$, in (26) is used

$$P_k = P_0 \left(\frac{\lambda}{\mu}\right)^k \frac{1}{n! n^{k-1}}. \tag{26}$$

Based on the observations above, if we define a parameter α to denotes the utilization of a server, we get (27). This transforms (25) and (26) into (28)

$$a = \frac{\lambda}{n\mu} = \frac{\rho}{n} \tag{27}$$

$$P_k = \begin{cases} P_0 \frac{\rho^k}{k!}, & \text{for } k \leq n \\ P_0 \frac{a^k n^n}{n!}, & \text{for } k > n. \end{cases} \tag{28}$$

In this case, P_0 can be reformulated as

$$P_0 = \left(1 + \sum_{k=1}^{n-1} \frac{\rho^k}{k!} + \sum_{k=n}^{\infty} \frac{\rho^k}{n!} \frac{1}{n^{k-1}}\right)^{-1}. \tag{29}$$

Since the targets distribution follow a Poisson law, the probability that a target has to wait before it is covered is given as

$$P(\text{waiting}) = \sum_{k=n}^{\infty} P_k = \sum_{k=n}^{\infty} P_0 \frac{\rho^k}{n!} \frac{1}{n^{k-1}} = C(n, \rho). \tag{30}$$

From the above, we can calculate the performance metrics as follows.

1) The average queue length can be formulated as in (31). This is the average number of targets in the system waiting to be covered

$$\bar{Q} = \frac{\rho}{n - \rho} C(n, \rho). \tag{31}$$

2) The number of busy sensors can be formulated by (32). This signifies the number of sensors that are not available at a particular time during coverage because they are already covering a target

$$\begin{aligned} \bar{n} &= \sum_{k=0}^{n-1} k P_k + \sum_{k=n}^{\infty} n P_k \\ &= P_0 \left(\rho \sum_{k=0}^{n-2} \frac{\rho^k}{k!} + \frac{\rho^n}{(n-1)!} \frac{1}{1-a}\right) \\ &= \rho. \end{aligned} \tag{32}$$

3) The average number of targets can be formulated by (33), i.e., number of targets either being covered or waiting to be covered

$$\bar{N} = \rho + \frac{\rho}{n - \rho} C(n, \rho). \tag{33}$$

This is understandable since a target is either in the queue waiting to be covered or it is already being covered.

4) A target has to wait if at time t, the number of sensors in the system is at least n. Thus, the time while a target is being monitored is exponentially distributed with parameter $n\mu$, and if there are $n + j$ targets in the system, then the distribution of the waiting time can be formulated by (34), which can be generalized by

$$\begin{aligned} f_W(x) &= \sum_{j=0}^{\infty} P_{n+j} (n\mu)^{j+1} \frac{x^j}{j!} e^{-n\mu x} \\ &= P(\text{waiting}) n\mu (1 - a) e^{-n\mu(1-a)x} \end{aligned} \tag{34}$$

$$F_W(x) = 1 - C(n, \rho).e^{-\mu(1-\rho)x}. \tag{35}$$

The mean waiting time is formulated

$$\bar{W} = \frac{1}{\mu(n - \rho)} C(n, \rho). \tag{36}$$

5) The response time is the sum of the waiting time and the service time. Therefore, the distribution of the response time is calculated as in (37). Consequently, the average response time can be calculated by

$$\begin{aligned} f_T(x) &= P(\text{no waiting}) \mu e^{-\mu x} + f_{W+S}(x) \\ &= 1 - P(T > x) \end{aligned} \tag{37}$$

$$\bar{T} = \frac{1}{\mu} + \bar{W}. \tag{38}$$

6) The utilization of a single sensor is formulated as in (39). The overall utilization of an n-sensor system is also given in (40). This gives the total number of sensors used during the entire coverage process

$$U_s = \sum_{k=1}^{n-1} \frac{k}{n} P_k + \sum_{k=n}^{\infty} P_k = \frac{\bar{n}}{n} = a \tag{39}$$

thus the overall utilization of n sensors is given as

$$U_n = n U_s = \bar{n}. \tag{40}$$

7) The system is said to be idle if there are no available targets to be monitored else the system is busy. $E\delta_r$

Algorithm 1 Target Coverage

Input: λ, μ

Output: Coverage result. This is usually dependent on the purpose for coverage.

d is the required threshold for any sensor to be busy

Initialization :

From the transition probability determine the number of targets $N(t)$

Initiate the arrival of sensors into the system at time t

Calculate the mean number of targets to be covered, $\bar{N}$

Calculate the sensor utilization factor U_s

LOOP Process

for $i = 1, \ldots, n$ **do**

  if $(S_i \textit{ is busy})$ **then**

    Calculate the mean busy period $E\delta$

    if $E\delta < d$ **then**

      wait

    else

      Assign to S_{i+1}

    end if

  end if

end for

return

denoting the mean busy period of the system can be formulated as

$$E\delta_r = \frac{1 - P_0}{\lambda P_0} = \frac{1}{\mu - \lambda}. \tag{41}$$

Equations (29)–(32), (34), (35), (37), and (39) are the required models for our algorithm.

In the next section, we present the algorithm for target coverage in detail.

E. Target Coverage Algorithm

From the models developed in the previous section, we propose an algorithm for target coverage as shown in Algorithm 1.

Using the transition probability we can determine the number of targets to be covered. While doing this, sensors keep arriving to the area. It is worthwhile noting that, these sensors are embedded in the mobile devices carried about by mobile users. Based on time constraints, it is necessary for us to calculate the mean number of targets to be covered. This is necessary as it will help save time and reduce redundancy, i.e., if covering less amount of target will give a required result, then there will be no need tasking all sensors to cover many areas.

Meanwhile, we calculate the mean queue length too. This will give us an idea of how many targets that are waiting to be covered by the sensors.

Let us assume n sensors enter the system, and are in close proximity to a target, then the following rule applies.

Rule: In case of multiple sensors in close proximity to a target, the sensor with highest signal strength should cover the target.

Next, we calculate the sensor utilization factor to know how the sensors are being utilized by the targets.

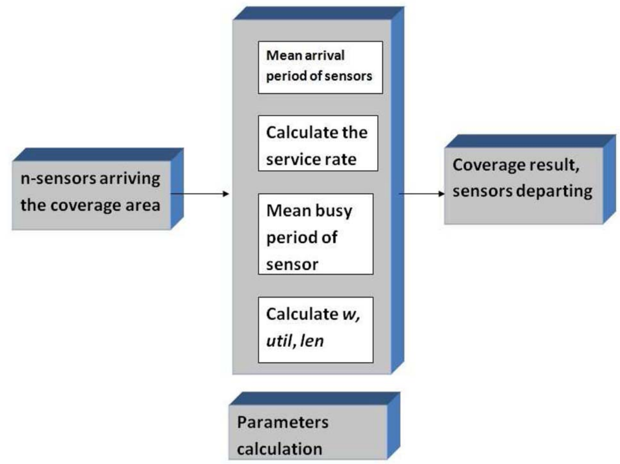

Fig. 4. Queuing process in MCS.

We later calculate the average waiting time of covering a target. This is important as it attaches time to the period a target gets covered. Because a lesser coverage time implies higher efficiency in the system. If a sensor is busy in the system, its next intended target is automatically passed to the next available sensor.

IV. Evaluation

A. Methodology

We simulate a network with incoming sensors and target points randomly located in a 3 by 3 square km area. The general flow of the entire queue process is given in Fig. 4.

The first block of Fig. 4 represents the number of sensors that have arrived the queue system getting ready to cover the targets.

The next block is for parameters computation which has w, util, len, and other parameters. w represents the average waiting time a target has to wait in the system before it is covered; util represents the sensor utilization and len represents the queue length.

The coverage result block represents where the result is sent. This could be either to a base station or a central server for decision to be made. Also, this is the point where sensors that have already done their jobs exit the system.

B. Simulation Results

We start our simulation using 200 sensors that arrive at the coverage area which contains 50 stationary targets. We arbitrarily assumed a threshold, d, of four targets for a sensor to be deemed busy. From the simulation, we discovered that the average waiting time for a target to be monitored normalized to 0 s as the number of sensors increases. In fact, from the arrival of the 15th sensor up to the 200th sensor, the targets no longer need to wait to be covered. This can be observed in Fig. 5.

Fig. 7 shows the average time a target is in the system. That is the average time before it is discovered by any present or arriving sensor, which seems to be approximately 0.2 s.

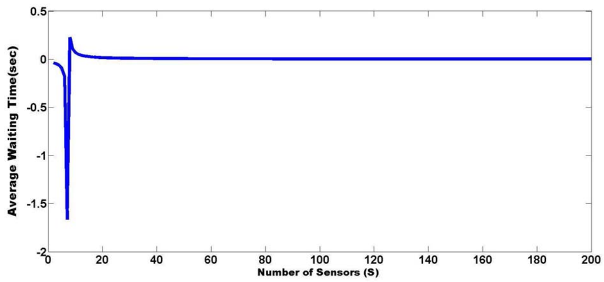

Fig. 5. Average waiting time versus the number of sensors.

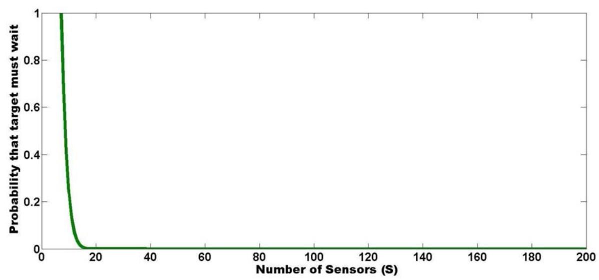

Fig. 6. Probability that target must wait versus the number of sensors.

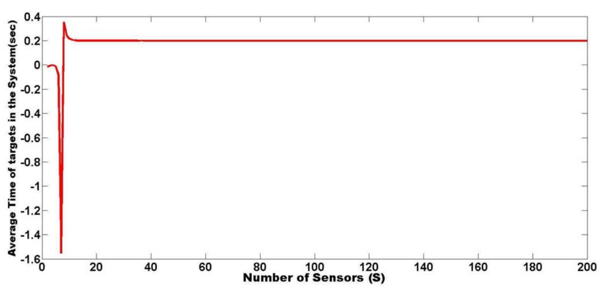

Fig. 7. Average time of targets in system versus the number of sensors.

Fig. 6 shows that the probability that a target needs to wait for an available sensor to cover it is 0. In other words, there are no busy sensors at that particular time as such every target gets covered almost immediately.

Fig. 8 shows the mean busy period of the whole system against the waiting time and this is also 0 which is almost similar to what we observed in Fig. 5. What this implies is that, the average time a sensor is busy is quite minimal. This can be explained as a result of many sensors already in the coverage system as such there may appear to be many idle sensors. Furthermore, Figs. 5 and 8 show a negative status for time when the number of sensors is less, this is due to the fact that more sensors are required for the model to work effectively. It is worthwhile noting that real crowd sensing application requires participant population to be greater than a certain threshold. Therefore, this observation complies with the reality. On the other hand, as the focus of this paper is effective target coverage and average waiting times, we include investigation of this lower bound in our future research agenda so that this behavior can also be better understood.

Table II shows a summary of the simulation results.

TABLE II
SUMMARY OF SIMULATION RESULTS

Parameters	Values
Coverage Area	3 x 3 km
Number of sensors	200
Number of targets	50 (Stationary)
Probability of waiting	0
Average time before discovery	0.2 Sec
Mean busy period of system	0 Sec
Mean busy period of sensors	0 Sec
Coverage time	0.00001 Sec
d, threshold	4 targets

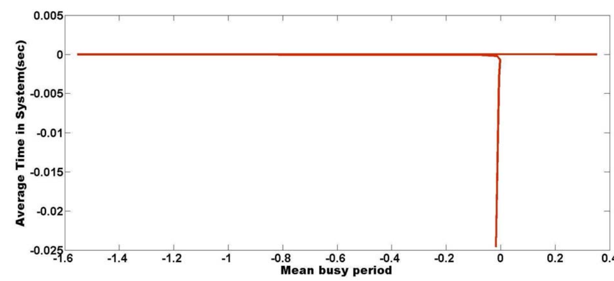

Fig. 8. Average time in system versus the mean busy period.

Based on these results and figures, the system automatically decides on the next step by using Algorithm 1. This decision includes assigning a new sensor to cover a target immediately upon the arrival of a new sensor in the coverage area. Once this decision has been made, the result is sent to the base station or the central platform for onward decision making purposes.

In terms of comparison, previous methods mentioned in Section II did not provide platforms for sensor scheduling in target coverage, our method, however, provides this. In particular when compared to [30] which focused mainly on energy problem, our method takes into cognisance all factors (which include queue length, average wait time, etc.) required for effective target coverage as opposed to theirs. Moreover, our proposed method also highlighted various required parameters and their overall importance in target coverage.

V. CONCLUSION

In this paper, we have focused on the target problem faced during MCS. With this in mind, we have proposed a queuing model-based algorithm from the birth-and-death mechanism to solve the coverage problem in MCS. According to the proposed model, the sensors arrive the coverage area in the form of a birth process, cover the target and exit the coverage area in the form of a death process. We have first developed the necessary queue models required for the algorithm to be implemented. The simulation results showed an average wait time of 0.2 s for a target to be monitored and the attendant result to be sent. Furthermore, we have found out that the probability that a target must wait is 0, meaning the amount of sensors in the system are enough for effective coverage.

In our future work, we intend to fully investigate the negative time issue, further explore the full applications of these developed models, creating a possible scenario for grouping sensors and targets to see how resources could be further managed in crowd sensing for effective decision making.

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