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RESEARCH ARTICLE

Efficient Mobile Crowdsourcing for Environmental Noise Monitoring

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ABSTRACT Governments and commissions all around the globe have worked on developing policies and rules as well as actions and measures for continuous assessment and remedies for environmental noise pollution. All of which requires continuous and accurate measurements of noise levels. The advent of smart city and IoT-based monitoring makes it possible for different technologies to cooperate in collecting and reporting environmental noise levels for longer duration and wider geographical region. Among others, mobile crowdsourcing (MCS) appears to be a promising technique for environmental noise monitoring with minimal upfront cost and almost no recurrent cost for regulators. This is due to the assumption of voluntary participation from mobile device owners who may be reluctant to participate if the recurrent cost of mobile resource consumption is high. In this work, an approach to improve mobile device resources efficiency for mobile crowdsourcing application in environmental noise monitoring is proposed. That is, noise samples from a device are collected only if it is significant to the accuracy of the measurements. Also this paper defines and mathematically formalizes the problem under study and develops two algorithms to optimize both resource and measurements efficiency. The results demonstrate the efficiency of the proposed solution.

INDEX TERMS Environmental noise monitoring, mobile crowdsourcing (MCS), measurement sampling.

I. INTRODUCTION

The expanding urbanization layout and industrial development have contributed significantly to the increase in pollution, in it all forms. Nowadays, noise pollution has become a major environmental problem and a major threat to human quality of life as well as all other living creatures. World Health Organization (WHO) classifies acoustic noise as the second source for environmental pollution.

Airport, cars and trucks (traffic), construction sites, and factories are considered the major sources for noise pollution. The impact of this pollution exceeds annoyance and inconvenience. Scientific research has accumulated epidemiological evidence of the adverse health impact of noise pollution. Frequent and prolonged exposure to high noise levels may lead to sever health conditions such as cardiovascular diseases, depression, hypertension and nervousness, sleep disorder, mental health, and potential hearing loss [1]–[4].

In order to combat with noise pollution, many decision makers (*e.g.,* governments and city municipals) have developed national and local regulations to restrain noise pollution levels [2], [5]–[7]. The first step was to define limits/boundaries for acceptable noise levels for different areas and times of the day. Then, there should be some sort of reporting mechanism. In the old days, people can raise a complaint about abnormal sound activities in their surrounding perimeter. Nowadays, sophisticated software solutions are commonly used to estimate noise levels in a city based on multi-parameters numerical models. For example, noise levels can be estimated using multiple factors such as road width, road segment utilization, traffic level, presence of noise sources …etc [8], [9]. Eventually, a noise map can be generated and reported to the decision maker who may take decisions based on discovered/detected incidents [10]. While these solutions have some merits, they involve assumptions

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and lack accuracy as no empirical real measurements are collected, especially that abnormal noise incidents can be momentary or imperceptible to these models.

Noise pollution management may involve multiple decision making actions such as traffic rerouting and scheduling, urban planning and site engineering, acoustic isolation and noise reduction, and noise level enforcement. The effectiveness of such a decision is highly dependable on the presence of continuous and precise monitoring of noise levels at the specified location or region.

Typical requirements for a noise monitoring system include accuracy, reliability, cost-effectiveness, scalability, power efficiency, reportability, representativity. In a measurement-based noise monitoring system, noise level is typically measured by a sound level meter (SLM) device which is basically an acoustic sensor. The sensor captures multiple sound pressure samples per second and can also provide averaged results over a desired period of time. Many of these devices are also supported by data storage, processing capability, and a communication module to report collected measurements. The packaged system typically encompasses proprietary software and hardware. The accuracy, reliability, robustness, and solutions offered by the device and the packaged system define its cost range, which can reach up to few tens of thousands dollars.

In order to assess the noise level of a city, authorities need to deploy these noise monitoring devices across the city, ending up paying huge amount of money not only for the cost of the devices but also for installation and maintenance. In an effort to improve noise mapping, many researchers have focused on developing more practical solutions to noise mapping such as Wireless sensor networks (WSN) and mobile crowdsourcing (MCS).

In an acoustic WSN, a network of small low-cost low-power acoustic sensors is deployed throughout the monitored region. Low-cost sensors can continuously provide acceptably accurate and reliable measurements of sound levels [11]–[13]. Albeit cheaper than previous option, it is still not a scalable approach as covering the whole city/metro area burdens city authority with unjustifiable installation and maintenance costs.

Mobile crowdsourcing, on the other hand, relies on collecting sound measurements from mobile phones that are naturally spread throughout city sites. Mobile crowdsourcing offers more scalable approach to monitor a whole city or metro area. However, mobile phones owners tend to be reluctant to allow their devices to being continuously active (measuring and reporting data) for such purpose as this will deplete the device battery and allowable network data. One approach to handle this problem is to offer a motive for mobile users to voluntarily participate in the monitoring activities by reducing the frequency and amount time of the device is being in active state.

It is worth mentioning that ultimately multiple solutions can be purposefully utilized together within the same city. For example, proprietary stations can be installed at few strategic locations to provide accurate and reliable noise measurements but cannot be adopted for city-wide monitoring, then WSN is deployed to provide breadth in monitoring urban areas, and then MCS can be used to scale and monitor uncovered zones or spots at multiple levels of granularity.

In this work, we propose a *motivating* mobile crowdsourcing noise monitoring approach that is power efficient and representative. Specifically, we are proposing to minimize the number of spatial noise samples collected from mobile devices when the contribution of more samples to the measurement accuracy is insignificant.

The rest of the paper is organized as follows. Section II provides an overview of recent works on environmental noise monitoring. Section III introduces the adopted IoT-based crowdsourcing noise monitoring architecture followed by the formalization of the problem and the proposed algorithms in Section IV. Experimental results and the performance of the algorithms are detailed in Section V. Finally, Section VI addresses our conclusions.

II. RELATED WORK

Recently, there have been many proposals addressing the problem of monitoring environmental noise. Many of these proposals are aligned with the prospective of smart city, where ubiquitous IoT devices are extensively deployed to collect, relay, and analyze data from various sources. The literature is rich of noise monitoring system proposals that consider multiple arrangements of fixed stations, WSN, and MCS that can work isolatedly or collaboratively [14]–[20]

Bello *et al.* [21] presented an urban noise monitoring system that adopts WSN for collecting sound measurements from stationary low-cost sensor terminals, and applies data analytics and machine learning (ML) techniques to identify sound source and visualize noise maps. Similarly, Fernandez-Prieto *et al.* [22] designed and implemented a city-wide, long-term WSN-based noise monitoring system that connects and reports data to a private cloud. While the system is suitable for accurate noise mapping, the authors reported that power and WiFi outages and the need for manual reconfiguration are the main drawbacks of the system.

Nowadays, the pervasiveness of mobile devices equipped with sensors makes MCS more scalable approach compared to other alternatives. MCS enables collecting noise samples on wider geographic areas while attaining significant reduction of overhead implementation cost and time. Mobile crowdsensing is mainly based on real sensed noise level measurements rather than pure computational models. In terms of smartphones measurements accuracy and precision, many researchers have shown that smartphones crowdsensing can be used efficiently for noise mapping in urban environment. They show through experiments that mobile crowdsensed measurements are within acceptable range of difference compared to a calibrated sound level meter [23]–[26]. Microphones of any device are calibrated using sound calibrators which is done typically in laboratory. Nonetheless, smartphone can be calibrated computationally out of the laboratory. For example, it can done by comparing smartphone measurements to a reference calibrated sound level meter [27] or computationally by applying a correction vector to sound level measurements based on collected database of similar device model [24], [28].

In addition to calibration, it is necessary to collect large amount of noise samples with adequate spatial and temporal density that secures acceptable measurement error [26], [29], [30]. Nonetheless, some studies showed that even with intermittent monitoring, smartphones crowdsourcing can be effective if statistical methods are integrated [24], [31]–[33]. When multiple mobile devices densely cover a specific area, averaging devices measurements would provide a good estimate of the area average. The smaller the areas, the higher the precision of areas averaged noise values. As any other data collection systems, data sparsity is difficult to avoid in MCS. Thus an estimation mechanism has to be adapted for interpolation of missing location data. For example, Grubeša *et al.* [26], Zuo *et al.* [34] used the ordinary Kriging method to have full coverage (estimation) noise maps. Huang *et al.* [35] proposed a spatio-temporal correlation matrix to predict the value of missing points in crowdsensed noise mapping systems. Koukoutsidis [32] applied spatial sampling techniques to estimate the average of the environmental temperature. In a different manner, Can *et al.* [36] considered aiding fixed noise monitoring stations in estimating uncovered points by mobile measurements. They reported that the mobile measurements with spatial interpolation is efficient even using few and short samples. Quintero *et al.* [20], [37] suggested through field experiments a 34m radius for mobile samples aggregation to minimize estimation error.

In MCS, multiple contextual metadata can be reported along with collected sound samples. These data depicts the status and context of the device at the time of sound level measurements. The context of the device directly impacts the accuracy of the measured noise level. Rana *et al.* [38] reported a significant variation on the measured sound level when considering different context *e.g.,* handheld versus in-pocket device. The authors developed a classifier based on k-nearest neighbour to determine acceptable context. Zappatore *et al.*. [17] developed a ML algorithm that exploits context data to improve the efficiency of the crowdsourced data. It is worth to mention that taking context in account improves not only the accuracy of the data but also can improve the device resource consumption efficiency if the device is put on sleep when it is in unacceptable context.

Large scale monitoring would definitely result in large data aggregation, making cloud/edge computing suitable technology for handling MSC and WSN data. Zamora *et al.*. [15] suggested a generic architecture for smartphone crowdsourcing based on cloud solutions. They mapped many proposals in literature to this architecture. Longo *et al.* [25] developed a cloud-based platform for participatory noise measurements featuring web applications for users and city authorities. Sarma *et al.* [14] proposed a framework for scalable and collaborative hierarchical sensing and data collection using hierarchy of multiple size clouds (cloud, local, nano).

Many of the existing proposals presumes users are willing to voluntarily participate in collecting and reporting noise samples. However, having a smartphone continuously on active mode is resource consuming *i.e.,* battery, network data, and computing power) in addition to potential privacy exposure [35]. Incentive mechanisms are critical in motivating smartphone users to join the crowdsourcing, otherwise may not participate. Several research works investigating incentive mechanisms are summarized in [16], [33].

Determining the time and location of the measurements and selecting the set of reporting devices is an important issue that contributes to both accuracy and resource conservation. Zamora *et al.* [39] developed noise crowdsensing architecture, featuring precise temporal noise sampling with the aim of minimizing smartphone battery consumption. They developed a decision tree to optimize sampling precision and that algorithm takes into account the context and the status of the device to decide whether to collect samples from this phone or not. They reported a 60% reduction in smartphone resource consumption. Muthohar *et al.* [40], addressing the trade-off between accuracy and power efficiency, proposed an adaptive sampling technique that considers the motion of the device. Sarma *et al.* [14] considered compressive sensing to address scalability-accuracy trade-off. Lastly, Ben Said *et al.* [41] developed a deep learning framework that predicts the availability of crowdsourced service in a specific region based on historical spatio-temporal presence of mobile devices.

In summary, one can identify the trade-off between the number of active participant devices and accuracy, that is, the more reporters, the better accuracy, in addition to the trade-off between participant device activity and device resources efficiency, that is, the shorter and less frequent active periods for a device, the less power and network data consumption. This work tries to exploit this marginal intersection between the number of reporters and measurements accuracy to better improve mobile devices power efficiency.

III. THE PROPOSED ARCHITECTURE

The proposed architecture considers an IoT noise monitoring architecture comprising cloud infrastructure and heterogeneous sensing infrastructure comprising mobile phones and other sensing devices (*e.g.,* WSN) as shown in Figure 1. Mobile phones equipped with sound sensors run a sound level meter application (SLMA) and collect noise samples and report to the cloud server. The server maintains data collected from all mobile devices and the results are displayed as real time noise map to the decision maker.

Next, the basic features of the proposed approach are detailed.

A. ZONING

In the proposed architecture, a city (or a metro-area) should be first divided into multiple zones. Smartphones within a

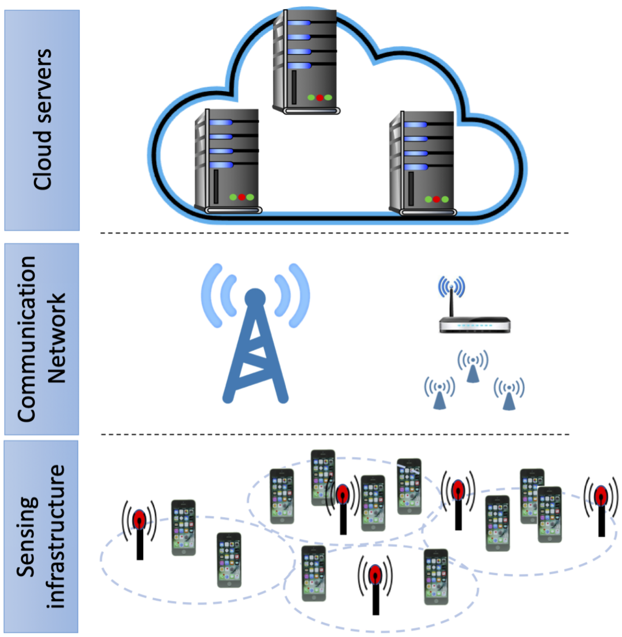

FIGURE 1. Proposed architecture.

zone should report noise measurements to the cloud server (one or multiple). For each zone, the server is responsible for determining which and when a device within a specific zone should collect and report measurements. The server should obtain the number of mobile devices within a zone, then its task is to periodically choose the minimum number of devices to report sound measurements.

For a given zone, the time is divided to slots. The length of a slot corresponds to sampling rate. On each time slot, the server sends a participation message to the selected devices within the zone. Lastly, all measurements and decisions for a zone are maintained and carried independently from other zones.

B. REPRESENTATIVENESS

When selected mobile devices within a zone report their measurements, the average value of these measurements represents the estimated value for the zone at a given time. It is conceivable to expect that the more samples reported, the more representative estimated average value for the zone, *i.e.,* the more samples reported, the more accurate estimation. However, it is arguable that in many occasions multiple samples are sufficiently equivalent and their effect on the estimated value is marginal. Hence, we leverage this hypothesis to minimize the number of actively reporting devices.

The server may start with an arbitrary number of participants. Then, it will try to decrease the number of participants to reduce power and data consumption or increase the number to improve accuracy. There should be some sort of feedback that directs the change of the number of participants. For instance, one can choose the variance in the averaged results collected from all participants, within a zone, to not exceed a given threshold. If it does, the number of participants increases in the next time period/slot. If the variance is too low compared to the threshold, the server may reduce the number of participants. Figure 2 illustrates the proposed approach.

TABLE 1. Parameters notation and corresponding values.

Parameter	Description
Z	Zone under monitoring
D_z	Set of participants mobile devices in zone z
M_z	Total number of mobile devices in the zone z
$K(t)$	Number of of selected mobile devices by the algorithms at time slot t
$n_z(t), n_z(t-1)$	Numbers of engaged (selected) mobile devices at current time slot t and previous time slot $t-1$, respectively
$n_{z,min}$	Minimum acceptable number of engaged mobile devices defined by the algorithm's user.
$sd_z(t)$	Standard Deviation of the measured noise level in zone z (in dB)
$sd_{z,threshold}$	The reference level for the Standard Deviation of the measured noise level in zone z (in dB)
$dB_{i,z}(t)$	The measured noise level on mobile device i located in zone z at time slot t
$dB_{\mu,z}(t)$	The mean (average) measured noise level among mobile devices located in zone z at time slot t
$T_{selection}$	Time for collecting sound level measurements by mobile devices; which is defined by algorithms' user.
$X_z(t), X_z(t-1)$	Vector of Binary Integer variables to identify mobile devices in zone z at time slot t and $t-1$, respectively
$X_{i,z}(t), X_{i,z}(t-1)$	Binary Integer variable to identify mobile device i in zone z at time slot t and $t-1$, respectively. Values are 1 for selected (engaged) and 0 for not selected (not engaged)

IV. OBJECTIVE AND OPTIMIZATION MODEL

The objective of the proposed approach is to minimize mobile phone recurrent cost, battery consumption and network data usage, while maintaining efficient monitoring. The sampling algorithm can implement multiple policies to achieve this objective *e.g.,* a device should not be chosen in two consecutive periods or for more than 1 minute. In addition, the aggregated number of samples reported to the cloud is also expected to be lowered substantially.

N.B. all variables and notations are explained in Table 1. Initially, assume there is a set of zones $Z = \{1, 2, \ldots, z, \ldots, L\}$ under monitoring and let $D_z = \{1, 2, \ldots, d_z, \ldots, M_z\}$ define a set of participants mobile devices who are in zone z. the main objective is monitoring the noise in zone z via least possible number of mobile

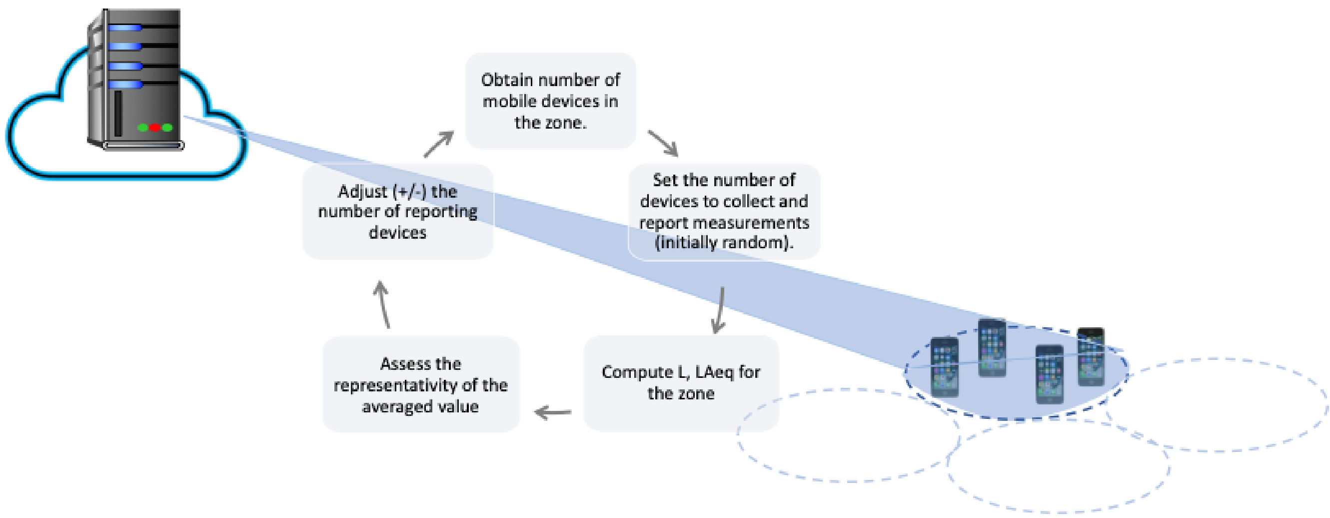

FIGURE 2. An illustration of the proposed approach.

devices in that zone. Therefore, the mean value of the measured noise from few number of mobile devices in the zone z at time t (denoted $dB_{\mu,z}(t)$) is considered. On the one hand, since we are calculating the mean value of the measured noise ($dB_{\mu,z}(t)$), we observe the variation on the *Standard Deviation ($sd_z(t)$)* and utilize it as a control measure on the crowdsourced measured noise. On the other hand, we are looking to reduce the number of selected mobile devices among participants in zone z. We use a binary integer variable $X_{i,z}$ to identify mobile devices that are available (exist) and selected (participant) in the zone ; where 0 refers to *exist but not participating* and 1 refers to the *existence and participation* of that mobile device (*i.e.,* $X_{i,z}(t)$). Consequently, the objective becomes the minimization of the number of participant mobile devices. In addition, a supportive policy is incorporated to achieve the main objective that is constraining the number of consecutive times an available devise is selected to participate within a given zone.

To achieve an efficient crowdsourcing monitoring measure that minimizes the number of participant mobile devices in a zone, we formulate our model as an integer linear optimization problem with the following objective function (1), as shown at the bottom of the page, that is to minimize the number of selected participant mobile devices (number of participants). To observe a feasible solution of the proposed model, six constraints were considered; *i.e.,* equations 2–7, as shown at the bottom of the page.

Constraint 2 computes the mean value of the measured noise (sound level) that is the sum of noise levels of all participant devices averaged on their number. Constraint 3 calculates the standard deviation based on the participant

$$\min \quad n_z(t) = \sum_{i \in M_z} X_{i,z}(t) \quad \forall i \in D_z, \forall z \in Z \tag{1}$$

$$\text{s.t.} \quad dB_{\mu,z}(t) = \frac{\sum_{i=1}^{M_z} \left(X_{i,z}(t) \cdot dB_{i,z}(t)\right)}{\sum_{i=1}^{M_z} X_{i,z}(t)} \quad \forall i \in D_z, \forall z \in Z \tag{2}$$

$$sd_z(t) = \sqrt{\frac{\sum_{i=1}^{M_z} \left|\left(X_{i,z}(t) \cdot dB_{i,z}(t)\right) - dB_{\mu,z}\right|^2}{\sum_{i=1}^{M_z} X_{i,z}(t)}} \quad \forall i \in D_z, \forall z \in Z \tag{3}$$

$$sd_z(t) \leq sd_{z,threshold} \quad \forall z \in Z \tag{4}$$

$$n_z(t) \leq M_z \quad \forall z \in Z \tag{5}$$

$$X_{i,z}(t) \in \{0, 1\} \quad \forall i \in D_z, \forall z \in Z \tag{6}$$

$$X_{i,z}(t) = 0, \quad \text{if } X_{i,z}(t-1) = 1 \text{ and } n_z(t-1) \leq M_z - n_z(t) \quad \forall i \in D_z, \forall z \in Z \tag{7}$$

mobile devices determined by the integer value ($X_{i,z}(t)$). Constraint 4 defines the threshold ($sd_{z,threshold}$) for the standard deviation of the calculated mean value ($sd_z(t)$). Based on the definition of the model, this constraint is responsible for tracking the accuracy in respect to sound level measurement. Constraint 5 defines the upper bound for the number of participant mobile devices to be fewer than or (at most) equal to the total number of mobile devices (M_z) currently available in the *z-th* zone. Constraint 6 is the integer variable definition ($X_{i,z}(t)$); which is set to 1 if the mobile device *i* is in zone *z-th* and participating (engaged) in the sound measurement, otherwise it is set to 0. Lastly, constraint 7 is a special condition to constraint 6 and is responsible for excluding any mobile device participated in the previous time slot (*t-1*) from the selection in next time slot (*t*). Constraint 7 is vital for the optimization model since it implements the aforementioned supportive policy. This constraint 7 efficiently controls the participation among mobile devices in the zone, which is activated when the number of participant mobile devices in the previous time slot ($n(t-1)$) is less than or equal to the current number of not selected mobile devices ($M_z - n(t)$). As a result, the model tries to reduce the usage of mobile devices in the crowdsourcing first by reducing number of participants and then by alternating and switching the engagement among the participants in the zone.

The following Algorithm 1 executes the proposed optimization model (1 - 7) with the goal of reducing the number of mobile devices engaged in the noise level measurements. The algorithm basically starts with initialization steps (lines 2-7), and then enters the monitoring and optimization phase (Lines 8-26). The initialization steps are related to resetting all variables to zero (Line 2) and sets the Boolean Integer matrices; *i.e.,* $X_z(t)$ and $X_z(t-1)$; to empty matrices or mathematically sets to $\emptyset$ (Line 3). Then, participant mobile devices in zone z are obtained and added to vector D_z (Line 4). Then, the Boolean Integer matrices, *i.e.,* $X_z(t)$ and $X_z(t-1)$, is filled with respective reference index i using *For-Loop* iteration (Lines 5-7). After that, the algorithm starts the continuous monitoring loop as listed in Lines 8-26. In the continuous monitoring loop, the algorithm re-obtains (similar to Line 4) the participant mobile device (*participants* $\rightarrow D_z$) and acquires the number of participant mobile devices (M_z) as first steps in the continuous monitoring (Line 9 & 10). These two steps are vital to keep tracking the existence of participant mobile devices in zone z. Based on the selected participant mobile devices (engaged mobile devices),[1] the algorithm calculates the averaged (mean) sound level $dB_{\mu,z}(t)$ and the standard deviation ($sd_z(t)$) for zone z (Lines 11 & 12, respectively); which are the optimization model constraints 2 & 3. Then, the migration of historical data steps; which are moving the Boolean Integer matrix and the number

[1]In the initial loop (or cold start), there is no selection; therefore none of participant was engaged in the calculation of the first loop. This will be updated afterward.

Algorithm 1 MCS-Based Noise Monitoring Algorithm

1: **procedure** Main Algorithm($sd_{z,Threshold}$, $n_{z,min}$, $T_{selection}$)
2: $n_z(t-1)$, $n_z(t)$, $sd_z(t)$, $dB_{\mu,z}(t)$ set to 0 ▷ Initialization
3: $X(t)$ & $X(t-1) = \emptyset$ ▷ Initialization
4: $D_z \leftarrow$ Obtain participant mobile device in the zone ▷ Initialization
5: **for** $d_i \in D_z$ **do** ▷ Initialization
6: $X_{i,z}(t) = 0$ and $X_{i,z}(t-1) = 0$
7: **end for**
8: **while** true **do**
9: $D_z \leftarrow$ Obtain participant mobile device in the zone
10: $M_z \leftarrow SizeOf(D_z)$ ▷ Get number of participants
11: Calculate $dB_{\mu,z}(t)$ ▷ Constraint 2
12: Calculate $sd_z(t)$ ▷ Constraint 3
13: $X_{i,z}(t-1) \leftarrow X_{i,z}(t)$ ▷ Move selection $(t) \rightarrow (t-1)$
14: $n_z(t-1) \leftarrow n_z(t)$
15: **if** $sd_z(t) > sd_{z,Threshold}$ **then** ▷ Constraint 4
16: **if** $n_z(t) < M_z$ **then** ▷ Constraint 5
17: $n_z(t) = n_z(t) + 1$
18: **end if**
19: **else**
20: **if** $n_z(t) > n_{z,min}$ **then** ▷ Minimum participants is required
21: $n_z(t) = n_z(t) - 1$
22: **end if**
23: **end if**
24: Selection($X_z(t)$, $n_z(t)$, $X_z(t-1)$, $n_z(t-1)$, M_z) ▷ Constraint 7
25: SLEEP($T_{selection}$)
26: **end while**
27: **end procedure**

of selected (engaged) mobile devices from timestamp t to timestamp $t-1$ as in Lines 13 & 14, respectively. Next is the implementation of constraints 4 & 5 in the nested *IF-THEN-ELSE* statements; which results in either an *increment* or a *decrement* by one, otherwise no change on the number of selected (engaged) mobile devices in time slot t according to flow of conditions (Lines 15-23). After that, the algorithm invokes the *Selection* algorithm 2 to comply the special performance constraint 7 (Line 24). Finally, the algorithm holds for collecting sound level measurements (Line 25); *i.e.,* sleep for period of time (as defined by the algorithm's user $T_{selection}$); before it repeat the monitoring steps (Line 26).

The *Selection* algorithm 2 is the procedure to identify which participant mobile device to be selected (engaged) in the sound level measurement for the upcoming time slot t, addressing in particular constraint 7. The *Selection* algorithm retrieves the two Boolean Integer matrices $X_z(t)$ & $X_z(t-1)$ with their defined number of selected participant mobile

Algorithm 2 Participants Selection Algorithm

1: **procedure** Selection($X_z(t)$, $n_z(t)$, $X_z(t-1)$, $n_z(t-1)$, M_z)
2:     $index = 0$ ▷ Initialization
3:     $S_{temp}(t)$ & $S_{temp}(t-1) = \emptyset$ ▷ Initialization
4:     **for** $i = 1, \ldots, M_z$ **do**
5:         **if** $X_{i,z}(t-1) = 1$ **then**
6:             $S_{temp}(t-1) \leftarrow i$
7:         **else**
8:             $S_{temp}(t) \leftarrow i$
9:         **end if**
10:         $X_{i,z}(t) = 0$
11:     **end for**
12:     **if** $n_z(t-1) \leq (M_z - n_z(t))$ **then**
13:         **for** $i = 1, \ldots, n_z(t)$ **do**
14:             **while** true **do**
15:                 $index$ = Random($S_temp(t)$)
16:                 **if** $X_{index,z}(t) \neq 1$ **then**
17:                     Break WHILE-LOOP
18:                 **end if**
19:             **end while**
20:             $X_{index,z}(t) = 1$
21:         **end for**
22:     **else**
23:         **for** $i \in S_{temp}(t)$ **do**
24:             $X_{i,z}(t) = 1$
25:         **end for**
26:         **for** $i = 1, \ldots, (n_z(t-1) - n_z(t))$ **do**
27:             **while** true **do**
28:                 $index$ = Random($S_{temp}(t-1)$)
29:                 **if** $X_{index,z}(t) \neq 1$ **then**
30:                     Break WHILE-LOOP
31:                 **end if**
32:             **end while**
33:             $X_{index,z}(t) = 1$
34:         **end for**
35:     **end if**
36: **end procedure** ▷ $X_z(t)$ is updated

devices, *i.e.,* $n_z(t)$ & $n_z(t-1)$, respectively, and the size of all participant mobile devices in zone z (M_z) as shown in Line 1. As initial steps, the algorithm defines a temporary variable named *index* that will holds the index of suggested (for selection) mobile device during the algorithm's process (Line 2). And it defines two empty ($\emptyset$) integer vectors namely $S_{temp}(t)$ and $S_{temp}(t-1)$ that hold the indices of participant mobile devices (Line 3). Through iteration among all participant mobile devices indices $(1, \ldots, M_z)$, the algorithm sorts and groups these indices into the two integer vectors ($S_{temp}(t)$&$S_{temp}(t-1)$) according to the selection of the participants on the previous time slot; *i.e.,* $X_{i,z}(t-1)$ (Lines 4-11). By the end of line 11, the algorithm would have two vectors with indices, one holds previously selected ($S_{temp}(t-1)$) and the other holds not selected ($S_{temp}(t)$) mobile devices. Next, the algorithm discovers the selection through nested *IF-THEN-ELSE* statement to meet the special constraint 7 requirement, namely avoiding previously selected mobile devices (Lines 12-35). The nested *IF-THEN-ELSE* statement goes through two level of checks. The high level checkpoints in the nested statement (Lines 12, 22 & 35) is related to the possibility of having only newly selected mobile devices for the time slot t. If the high level check is valid, then the algorithm randomly chooses $n_z(t)$ from the integer vector of not selected mobile devices ($S_{temp}(t)$) and mark them selected, precisely $X_{index,z}(t) = 1$ (Lines 13-21). If the high level check is invalid, then the algorithm implement two sets of steps. The first set of steps is set to 1 all mobile devices which has not been selected previously and that through retrieving all indices in integer vector $S_{temp}(t)$ (Lines 23-25). The second set of steps is selecting the remaining number of mobile devices to be forcibly engaged again in the sound level measurement. Consequently, the remaining selection is performed by randomly selecting $n_z(t-1) - n_z(t)$ indices from the integer vector $S_{temp}(t-1)$ and set them to 1 (Lines 26-34). By the end of the *Selection* algorithm, the Boolean Integer matrix for the selected (engaged) mobile devices $X_z(t)$ is updated for the time slot t (Line 36).

V. EXPERIMENT

The goal of the experiment is to validate the proposed model and algorithms. We consider in this experiment emulating a zone with multiple mobile devices and collecting simultaneously noise samples from these mobile device.

A. TOOLS AND EQUIPMENT

All participant mobile devices were of the same model and equipped with an off-the-shelf noise sampling application. The sampling application expresses the captured sound pressure in dB and reports both the equivalent A-weighted sound pressure level (LA_{eq}) for each second in dB and the maximum recorded sample (L_{max}). In the performed experiment, we considered the equivalent A-weighted sound pressure level (LA_{eq}) as it is more relevant to this experiment and the calculated mean value ($dB_{\mu,z}(t)$) in the proposed model.

B. RESTRICTIONS

In this work, there are restrictions applied on the proposed model and approach to efficiently operate. First restriction is when having extreme number of mobile devices in a single zone. This limitation is enforced to avoid the expansion of the feasible solution of the mathematical optimization model (objective function 1). Therefore, the work procedure (Figure 2) will readjust the zone size in case of unexpected sharply increase of number of mobile devices. Second restriction is selecting the time slot window t to be fairly short. Designating a long time slot windows such as 30 seconds or longer could raise several performance challenges. Longer time slot windows could effect the goal of energy efficiency by activating selected mobile devices

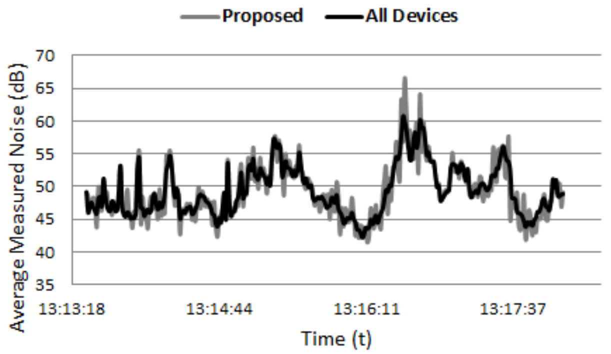

FIGURE 3. Averaged measured noise (in dB).

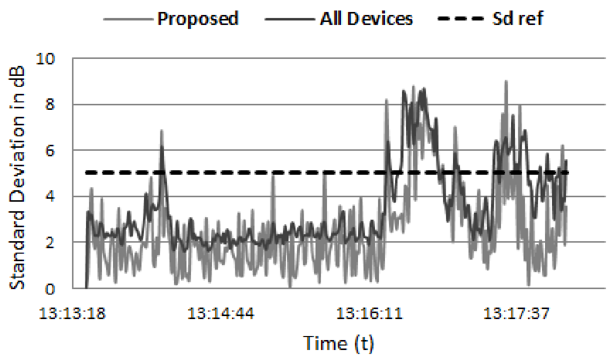

FIGURE 4. Standard deviation (in dB). $sd_z(t)$ is the calculated standard deviation and *Ref*. is the upper limit reference or the threshold of the acceptable standard deviation.

for longer time than others. Apparently, human behavior (e.g. suddenly quitting the participation) would escalate the challenge of mobile devices selections. Therefore, the time slot window t was 3 seconds. A time slot window of 5 to 10 seconds were tested and found acceptable however in this work results for a 3 seconds time slot window were reported.

C. RESULTS

Figures 3-7 show the results for 15 participant mobile devices (smartphones) running the application for 5 minutes.

Figures 3 and 4 plot the averaged noise level (primary goal of the proposal) and the standard deviation of the average noise (tuning parameter in the proposed model), respectively. Both Figures 3 and 4 have two lines which represents the observations when the proposed approach is used, in particular the adaptive mobile devices participation, (denoted **Proposed** and marked with gray line) and when all mobile devices are participating (denoted **All devices** and marked with dark line). As shown in Fig. 3, the proposed approach is able to monitor the sound level (noise level); comparably when all mobile devices are used; on an area populated by people with mobile devices. In the Fig. 3, the averaged sensed sound level in general varies between 40 and 60 dB across for both approaches during the experiment. In addition, there was a fairly increased sound level (up to 65 dB) between the time 13:16:15 and the time 13:16:40.

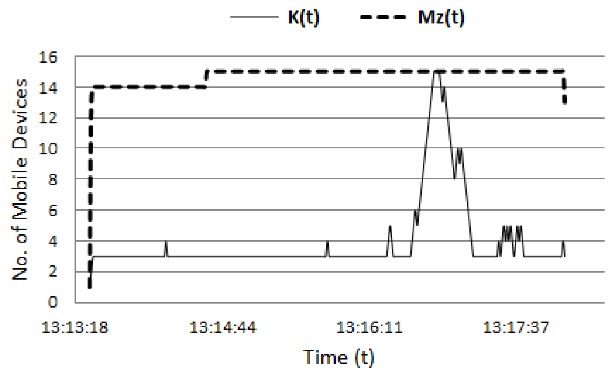

FIGURE 5. Number of participant mobile devices. $M_Z(t)$ is total number of participants and $K(t)$ is the selected (engaged) number of participants.

The scope of this paper is to sense the sound level rather than to control it, therefore, the scope of this experiment is limited to observe the sound level. On the other hand, in Fig. 4, we are interested to observe the standard deviation performance as it is vital for the proposed optimization model. In this experiment, we set the standard deviation threshold ($sd_{z,threshold}$); which is marked as dash-line *Ref.*; to 5 dB. Whenever the standard deviation ($sd_z(t)$) is higher than the standard deviation threshold ($sd_{z,threshold}(t)$), the number of selected (engaged) mobile devices is incremented, and the vice versa.

Figure 5 plots the number of participant mobile devices ($M_z(t)$) and ones which are actively collecting (engaged) and reporting noise samples ($K(t)$) throughout the experiment duration. In this figure, we observe that the number of selected mobile devices was mainly set by the algorithms to 3 engaged mobile devices; which is the minimum acceptable number of participants ($n_{z,min} = 3$); and only incremented during the mentioned period of fairly increase in sound level. Moreover, there were few incidences where the number of engaged mobile devices ($K(t)$) was incremented and that because the standard deviation ($sd_z(t)$) was very close to its reference upper bound limit ($sd_{z,threshold}(t)$), see Fig. 3.

Figure 6 plots three sample outcomes during the experiment which each sample shows the observed selected mobile devices (in dark marked mobile devices), the measured sound level (in dB at the top-left), and the calculated standard deviation (in dB at the top-right). In Figure 6, there are three sub-Figures which was observed at three different instance during the experiment, *i.e.,* sub-Fig. 6a observed at time 13:14:40, sub-Fig. 6b observed at time 13:15:06, and sub-Fig. 6c observed at time 13:16:41, respectively. At the two observations sub-Fig. 6a and sub-Fig. 6b, the model was depending on three mobile devices to monitor the sound level as the standard deviation was low (below the threshold 5 dB as in Figure 4). However, in the third observation, *i.e.,* sub-Fig. 6c, the model was engaging nine mobile devices as the standard deviation was high (clearly above the threshold 5 dB as in Figure 4). This Figure 6 is demonstrating the effectiveness of using Linear Integer Programming in the

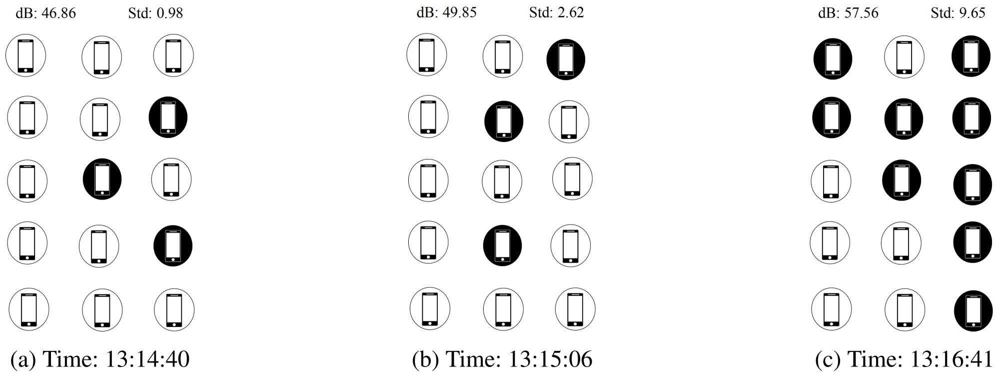

FIGURE 6. Three outcome samples during the experiment at time (a) 13:14:40, (b) 13:15:06, and (c) 13:16:41. The proposed optimization model is effectively switching among participant mobile devices as well as adapting the number of selected devices.

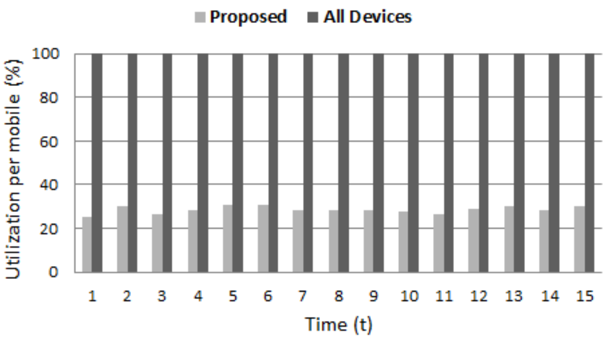

FIGURE 7. Utilization per participant.

proposed model as it is smoothly fulfill the targeted objectives in this work. The targeted objectives are (1) minimizing the number participant mobile devices used in monitoring the sound level, (2) avoiding the persisting feeding from mobile devices and circulating the sourcing among existing mobile devices, and (3) tracking the accuracy of measurements via observing the quality of calculated sound level indicator (in this model, we used the standard deviation).

Last and vital observation is shown in Figure 7; which reports the percentage of all participant mobile devices' utilization during the entire experiment duration. The motivation and the fundamental goal of this work is to reduce participant mobile devices' utilization while keeping the sensing performance in crowdsourced monitoring. In this Fig. 7, there are two bars reported per mobile device that was engaged in the experiment. The right dark bar represents the participation or usage duration (utilization) of the mobile device when all devices were participating in noise measurements. The left gray bar represents the participation or usage during (utilization) of the mobile device when the proposed approach was used. Despite the participate utilization were 100% for all mobile devices in the traditional approach, i.e. all devices are participating in the noise measurement, in the proposed approach all participant mobile devices were at most 30% of the sensing duration of the experiment. This vital observation is a key finding of the proposed model; *i.e.,* all participant mobile devices were engaged (selected) at most 30% during the experiment; because it is freeing the mobile device up to 70% of being used for crowdsensing.

D. DISCUSSION

This section discusses and compares relevant approaches to the approach proposed in this work. In the literature, many proposals presume that each participant mobile senses and reports noise measurements periodically *i.e.,* every specific period of time, focusing on accuracy and coverage and ignoring energy. Some works, however, have focused on developing energy and resource preserving approaches [42]. One approach is the context-awareness of a device which was mainly concerned with accuracy. However, Context-awareness can be utilized as a basis for determining whether a mobile phone should capture and report noise samples given its context [39]. This approach is able to maintain better measurements accuracy and avoid unneeded active periods for the devices. Compressive sensing is another approach that leverages correlation of sensed data and historical records to reconstruct/estimate missing data. This approach enables gathering measurements for large-scale area with only fewer data samples contributed by participants [43]. In addition, Sheng *et al.* [44] proposed a scheduling algorithm that minimizes the total energy consumption and ensures min-max fairness among participants. Simulation results show 80% reduction in total energy with minimum number of reports by each participant. This approach is only concerned with energy consumption and ignore accuracy of measurements as presumed that a single reading at a given zone is representative of the noise level at this zone. Similarly, Liu *et al.* [45] optimizes the number of samples required from each participant device based on its remaining energy level. In an alternative approach, Dutta *et al.* [46] defined a group mode in which participants who are in close proximity can send their measurements to an elected group leader who in turns reports the collected measurements to the cloud along with its own location. Hence, reduce the energy consumption

TABLE 2. A qualitative comparison between selected works.

Work	Approach	System	Accuracy	Coverage	Participants selection	Participants exclusion	Fairness	Comments
Dutta et al. [46]	Participants in close proximity can upload their measurements through an elected group leader.	Centralized	N/A	N/A	N/A	N/A	N/A	• Put burden on the leader • Groups rather than zone
Liu et al. [45]	Optimizes the number of samples required from each participant device based on its remaining energy level. It addresses accuracy and coverage by taking into account the number of samples and their distribution across multiple zones.	Centralized	A	A	A	N/A	N/A	• Prediction of participant movement trajectory • Assumed identical zone size.
Marjanović et al. [48]	Minimizes total energy consumption in a cell by selecting only k participants. It incorporates a utility function to rank monile within a given cell based on multiple attributes *e.g.,* Battery level, trustworthiness level, current state of the sensor (active/inactive)	Centralized	N/A	N/A	A	N/A	N/A	• Number of selected participants within a cell is constant/
Montori et al. [47]	Optimizes the ratio between the actual number of selected participants to the required number of participants as well as the fairness among the participants within a zone.	Distributed	AA	A	A	N/A	A	• Each mobile participates (or not) in the crowdsensing based on a defined probability adaptive to the coverage and fairness status in the zone. • Assumed the number of required observations is given.
Sheng et al. [44]	Scheduling algorithm with the aim of minimizing the total energy consumption and ensuring min-max fairness among participants.	Centralized	N/A	A	A	A	A	• Addresses the tradeoff between coverage and fairness • Zones are expected to be small as a single is considered representative of the zone
Xu et al. [43]	Leveraging compressive sensing, it enables fewer user contributions while maintaining acceptable accuracy	Centralized	A	N/A	A	N/A	N/A	• Aplicable to offline datasets only.
Zamora et al. [39]	Context-based decision about whether a mobile phone should capture and report noise samples given its context.	Distributed	A	N/A	N/A	A	N/A	• The main contribution was proposing an energy-efficient decision tree algorithm. • Accuracy is sought by excluding out of context devices from reporting.
Zhang et al. [49]	Minimizes total incentive payment by selecting fewer participant while satisfying a coverage constraint.	Centralized	A	A	A	N/A	N/A	• Assumed number of devices in cells follow power law distribution; nothing on the size of the cell.
This work	Optimizes the number of participants adaptively taking into account the accuracy of the last collected samples. In addition, it tries to achieve fairness by excluding participants from previous period from being selected again.	Centralized	A	N/A	A	A	A	–

[2]A: addressed, N/A: not addressed

of using GPS location and data transfer by the rest of group members. The approach can achieve significant energy savings as the group size increases.

A more relevant proposal to this work is in [47]. The authors try to optimize the ratio between the actual number of selected participants to the required number of participants as well as the fairness among the participants within a zone. Each mobile participates (or not) in the crowdsensing based on a defined probability adaptive to the coverage and fairness status in the zone. However, it is assumed that the number of required observations is given. Unlike [47], in this work the number of required samples is computed adaptively.

Lastly, Table 2 provides a qualitative comparison between this proposal and some selected works.

VI. CONCLUSION

In this work, we have identified a potential margin between power and data usage efficiency and measurement accuracy in mobile crowdsourcing for environmental noise monitoring. We introduced an adaptive approach to MCS noise monitoring that exploits this margin with the objective of improving mobile devices resource efficiency with acceptable measurements accuracy. The results show that the proposed model and the suggested algorithms were able to minimize the required number of mobile devices to monitor the sound level in an area. As a result, this minimization of the number of devices is vitally reducing the usage of participating mobile devices in crowdsourcing monitoring. The participating mobile devices were used at most 30% of the monitoring duration; which frees those mobile devices for up to 70% of the time.

For future work, we suggest incorporating machine learning (ML) techniques used to better estimate the required number of participants in each time slot (frame), and identifying and reasoning the source of the noise. On another dimension, one can be interested in studying the problem of adjusting the accuracy by adapting the size of the zones to the number and distribution of mobile devices.

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