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Novel MA-VFBC Based Deployment of Obstacle-Avoiding Scattered Sensors for Region-of-Interest Incidence Monitoring

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ABSTRACT The deployment of mobile and adaptive virtual force barrier coverage (MA-VFBC) classification scheme using a mobile emergency response and command interface (MERCI) platform that is functionally implemented to track and report incidences and consequent collateral damages to infrastructures within a region of interest (ROI) is proposed. Considering the enormous use of the global positioning system (GPS) devices for location data-gathering and processing, and its inherent limitations, the proposed GUI-based MA-VFBC platform is implemented using self-deploying and obstacle-avoiding scattered mobile sensor nodes. The GPS service is kept as alternatives, since only initial co-ordinates from where the deployed sensor starts to move and the maximum boundary location of the target location is considered. The practical experimentation work appraises the use and feel of the (MERCI) platform when integrated with the proposed novel MA-VFBC path-tracking classification schemes, while the simulation work investigates evident real-time system reliability issues as direction of node deployment with path distances, system computation time and system overheads in the presence of dissimilar multiple obstacles.

INDEX TERMS Emergency response, mobile and adaptive virtual force barrier coverage (MA-VFBC), MERCI, obstacle-avoiding sensor nodes, ROI incidence assessment.

I. INTRODUCTION

The large-scale deployment of smart platforms in various industrial spheres and domains to control actuators and to manage sensor nodes has rapidly evolved in recent years. In as much as recent research investigations have targeted the reportage and dissemination of critical information using smart platforms, only a few has however deployed smart platforms to identify detailed status of disaster occurrence [1]. The currently deployed platforms are technically deficient as a result of deploying redundant sensor path-tracking techniques, inefficient data-fetching and manipulation schemes, use of agile technologies and the incompatibility of these devices to modern software applications [2]. Little emphasis has been made to also self-deploy mobile sensors into disaster-prone or inaccessible locations using optimal path-tracking scheme as the proposed mobile & adaptive virtual force barrier coverage (MA-VFBC) scheme.

Since a disaster-prone region of interest (ROI) play a pivotal role in incidence tracking using mobile sensor nodes, quite a few research investigations has implemented and targeted the resulting inadequacies of the coverage area classification algorithm, which promotes the flooding of the entire ROI space with as many nodes as possible [3]–[5], rather than investigating the MA-VFBC classification scheme which, not only flood the entire ROI area with sensor nodes, but additionally allow these sensors to detect and protect the system's wireless sensor network (WSN) by forming a virtual force-like barrier or obstacles to ward-off un-permitted access to the WSN system [6], [7].

This approach is presented with three fundamental scenarios modeled around recent research works in the field

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of self-deploying mobile sensor nodes. The path-tracking algorithm is focused on the deployment of mobile sensors in an outdoor, indeterminable and disaster-prone environment.

The first scenario focuses on the deployment of the mobile sensors in situation where there are either multiple obstacles or no obstacles in the line of sight of the deployed sensors and the target location. This scenario suggests that an unhealthy or unsafe place can easily be reached by the beacon or robot-assisted mobile sensors with minimal hindrances, while the timing to reach the desired target location becomes minimal in cases of no obstacles in contrast with visible obstacles.

In the second scenario, since the use of global positioning system (GPS) devices as main tracking device predominates recent research works. While it is agreeable that these devices are widely and globally used, likely limitations are however enormous. These includes inability to correctly determine the location coordinates, to signal unavailability in ROIs. Our proposed technology is best fit for this situation as it does not require GPS service for calculating the robot's position, but requires only the initial co-ordinates from where it starts to move and the maximum boundary location of the target location for the sensor deployment.

Thirdly, coverage is one of the few prominent parameters used to measure the performance of any deployment algorithm. Network energy constraints and unreliable network channel are some common issues associated with limited sensing range [8]. Hence, a scalable algorithm has to be executed on the robot so that it can provide better performance for increased areas and increased number of obstacles. The MA-VFBC scheme as investigated and introduced in this article is such that covers a square wide area of 300m, however these techniques come with trade-offs when implemented in different applicable scenarios. The later part of this work presents the deployment techniques, with the resulting and applicable trade-off scenarios.

The evident research inadequacies using the mobile & adaptive-virtual force barrier coverage (MA-VFBC) approach have prompted our contributions in this letter which are now highlighted as follows:

1) Design and deployment of a stand-alone mobile emergency response and command interface (MERCI) platform to track and report incidences in a ROI area.
2) Integration of MERCI with the three novel MA-VFBC schemes, which self-deploys obstacle-avoiding scattered sensor nodes in region of interest (ROI) and across dissimilar-shaped obstacles was achieved.
3) Performance evaluation of the novel MA-VFBC path-tracking schemes was presented, while their comparative analysis w.r.t computation timing, mean node localization, maximum path and obstacle distances were all deduced. System overheads such as look ahead with goal angle and orientation were also investigated.

The rest of this work was elaborated with the work's preliminaries and related works in Section II. An appraisal the MERCI system model to track and report incidences is discussed in Section III, while Section IV focuses on the three proposed mobile and adaptive virtual force barrier coverage (MA-VFBC) schemes. Section V elaborates on the strategies for sink node deployment, detection and tracking of the target node, and Section VI evaluates the performances of the GUI-based MA-VFBC system. Conclusion and future direction is drawn in Section VII.

II. PRELIMINARIES AND RELATED WORKS

Numerous investigative works focusing on real-time energy aware mobile sensor deployment using robot-assisted sensor devices such as Dhondge *et al.* in [9] who proposed a heuristic and opportunistic link selection algorithm called as HOLA, which not only reduces the overall energy consumption of an IoT sensor network, but also balances it across the network. However, their work did not present in detail, the results of their approach. Also, since the paper tries to focus on the data aggregation as well, it however does not see any need to consider analyzing the scheduling of the networked control system and its allowable delay bound as expatiated by D.S Kim in [10].

Bartolini *et al.* in [11] laid emphasis on the vulnerability of mobile sensor deployment using the Voronoi- based approach to propose two new secure deployment algorithms in order coordinate the mobile sensors and to guide their movements. Maboubi *et al.* in [12] proposed guaranteed Voronoi diagrams for location error estimation of sensor deployment with assumed upper bound localization errors. However, these two similar Voronoi-based works are beyond the scope of this research works, as much preference in this works is targeted at the path-tracking methods of mobile sensor deployment, rather than focus on related vulnerability issues of the sensor deployment. Hence, this work simulates in advance as shown in the simulation results using more detailed parameters the mobile sensor and its deployment.

An optimal criterion for the sampling paths of a typical mobile robotic sensor was designed by Nguyen *et al.* [13] in their research works, but their works focused on data gathering in noise-less data locations. This is however not practicable, especially when a disaster-prone location is being considered. The issue of heterogeneous sensor monitoring were tackled by Lin *et al.* in [14], using an enhanced deployment algorithm. Their works emphasized on a monitored area and with the use of GPS device, which incidentally is not our focus in this work. A gradient-based approach with a distributed algorithm that allows for data exchange among sensors using location information was proposed by Habibi in [15], which is not covered in our own research scope as well. A speed prediction model to track the sensors was investigated by Basyoni *et al.* in [16], while a zoning-based tracking technique over Wi-Fi and using belief function was implemented by Alshamaa in [17], to properly ascertain the target area.

An analysis of the numerous routing protocols and its embedded efficacy [18], location and the numerous constraints or challenges posed by these locations were all considered by authors in [19], [20], while a holistic approach as to the compatibility of the mobile deployment in a 3D environment or other virtual realities were harnessed by authors in [21], [22]. The suggested performance techniques and analysis by these authors were however not feasible as they did not focus on real-life location and scenarios, but a virtual one, which is clearly not the focus of this work.

The Authors identified as Batalin and Sukhatme in [23] postulated a least recently visited (LRV) algorithm, where recently visited locations of deployed sensors are suggested to a newly assigned one. The algorithm is maximal in terms of sensing coverage; however, they do not implement a controlled movement and catchment for a considered region of target or interest. Xu and Qian [24] research works focused on novel localization approaches, which are simply used to estimate location of wireless sensor networks using mobile beacons. Their techniques are not suitable for our research work as it focuses only on node localization rather than robot-assisted mobile sensor deployment. Dhillon and Chakrabarty [25] in their approach, presented algorithms to deploy sensors in a location. Their algorithm also optimized the detection probability to be exponential to distance between the target and the sensor. However, their work did not focus on deploying robot-assisted mobile sensors with considerations to obstacles in an environmentally challenging or unsafe location.

In a related research work, Howard *et al.* in [26] presented a greedy method of sensor deployment in a maximum coverage region, but the drawbacks still remain their use of GPS network, while the target or interest points was inconclusive and remained undefined. A queuing algorithm based on birth-and-death models for effective target coverage proposed by Obinikpo *et al.* in [27] was introduced for mobile crowd sensing in order to determine the waiting time of target, the mean busy period and idle period of the deployed sensors. While an NP-hard problem was evidently resolved in [28], in other to guarantee a defined lifetime for the sensor nodes for unspecified networks.

The use of unmanned aerial vehicles (UAVs) was postulated by Corke *et al.* in [29]. They were able to deploy about 50 sensor nodes on a marked grass field of 7 grid, using what they termed as AVATAR (autonomous copter), Their results showed disparities in both manual and autonomous comparison, while more than one AVATAR has to be used at a time to deploy and learn the sensor network. An autonomous and heterogeneous sensor deployment system using unmanned aerial vehicles to deploy mobile and immobile sensors in a typical seismic location was proposed by Srikanth *et al.* in [30]. They focused on comparative analysis with the traditional techniques in terms of cost and time reduction. Our research direction considers these investigations highly, as effort to ensure a practicable implementation of our works is paramount.

Lei Zuo in [31] developed an adaptive spatial estimation algorithm to approximate a density function. His approach investigates that the density function which usually characterizes the distribution of the information of interest in a typical mobile sensor network domain is unknown. A point of interest algorithm was introduced by the authors in [32], [33], with the use of a relative neighborhood graph which is a globally acclaimed standard for localization-related issues in the absence of a GPS network. When typical wireless sensor networks (WSN) are compared with the traditional network approach, a renewed preference for WSN becomes undoubtedly higher.

A look at a practicable way of maintaining the power duration and consequent power consumption of the deployed mobile sinks are also issues of great concern in this work. Rao *et al.* [34], [35] in their works considered an optimal scheduling of mobile vehicles to travel along the shortest Hamiltonian cycle or path, hence eliminating an obvious trade-off of the resulting charging distances and angle between the mobile vehicle and the sensor nodes. Similarly, Jiang *et al.* in [36] proposed the joint use of mobile charges (MCs) depot positioning technique, together with their respective charging tour planning, in order to solve or minimize the number of deployed MCs and to rapidly increase the rate of charging time over the total traveling time. However, Xu *et al.* in [37] emphasized on the need to reduce service cost using a novel approximation concept of efficient scheduling of multiple MCs.

III. SYSTEM MODEL

A. MERCI PLATFORM

The development of mobile emergency response and command interface (MERCI) allows emergency responders to make quick and accurate incidence damage assessments following a natural disaster. The platform's life cycle as shown in Fig. 1, revolves around the GPS positioning, while the design, development and deployment of MERCI platform as depicted in Fig. 2 shows the inspector, that is dispatched to the marked disaster area, in order to gather multimedia information in the form of texts, pictures and sizable videos. Information are then manipulated by the system admin, who details the extent of damage and proffers repair works accordingly. MERCI is considered as a lightweight, high configurable application, and is easily integrated with other enterprise systems such as the proposed MA-VFBC scheme. MERCI is well-equipped with additional features such as the use of existing damage assessment forms or creates custom forms to fit-in for special requirements, Linking all Geo-referenced photographs, videos and assessments together. It also auto-populates data fields for property revisits, embedded with built-in reports and queries to calculate real-time damage estimates, spatial distribution of damage and mapping interface with visual display of different types of assessments, and improving resource allocation with optimal path-planning approach.

B. THE SERVER-SIDE AND DATABASE ANALYSIS

The keyhole markup language (KML) Creator class was designed to illustrate the map readings using Google map

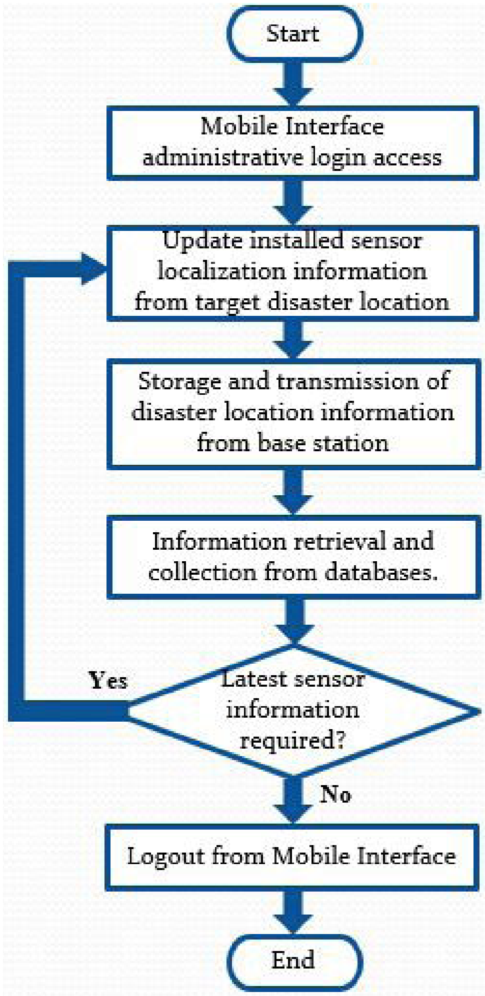


FIGURE 1. **The Cycle of the proposed GUI-based MA-VFBC platform.**

application program interface (API). The introduced vector class in the KML creator class calculates regional state or position. MERCI is implemented using JavaScript object notation (JSON) object to communicate with other applications and databases while the EDAJsonData class is designed to save and update data in the database. When data is sent from inspector, the server-side application extracts data from the sent JSON object using OceanitJson class and then simultaneously saves or updates the data in database system. To download data from the database, EDAOceanitData class was designed. To manage file I/O, uploads and downloaded file, OceanitFile class was designed. The OceanitUser class is designed to manage user information such as checking user-names of systems or sessions. The OceanitData class is designed to manage connection with structured query language (SQL) server, system configuration, data table for SQL, and etc. Finally, the ImageUtility class is designed to re-size image and get information of image.

The database structure of MERCI consists of elementary tables that are designed to accommodate unbounded amount of data. The database also includes embedded secondary tables that are designed to accommodate specific amount 6 The elementary tables used in the database compiles the assessment, incident and inspector tables as shown in Fig. 3.

C. DATA EXCHANGE BETWEEN GUI AND SERVER-SIDE

The JSON link structure is used as the communication link between the MERCI-GUI application and the server-side application. After login requested in initiated, login request parameters is sent to the server side application, then the JSON objects is sent as response, just as shown in Fig. 4. The value of ''authenticated'' inform the result of login request. If user send correct id and password to server, the value of ''authenticated'' is ''1'' and else is ''0''. It shows user get permission of revise and update data in the server or not. Fig. 5 shows the JSON object to report positioning data of inspector.

The JSON object include ''longitude'', ''latitude'', and ''timestamp'' to specific position of inspector. This information support effective measurement of disaster damage through providing correct position to user. Before implementing core function of application, user interface is designed for identifying function to implement. The mobile application of MERCI provides incident-list retrieval function. As a response to retrieving request, the JSON object is then sent to the mobile application. The value indicated as ''total'' informs about the number of incidents while the value indicated as ''results'' includes information of each incidents.

The mobile platform receives incident list and extracts data from JSON object. The inspector grasps incidents after this process. To figure-out the list of inspector, the server sends list of inspectors to the mobile platform using JSON object. The list of inspector includes detailed information of inspectors such as name, phone number, etc. To post an assessment onto the server, the mobile platform generates data, JSON object and includes disaster information. The JSON object for the assessment post is also used to retrieve the assessment list. The differences in the JSON object w.r.t the assessment posting and the information retrieval is known as the ''total'' and the ''type'' values. The ''total'' values declares the number of incidents, while the ''type'' value declares the type of response.

The user interfaces divided as language setting, login, network setting, report assessment, and general application setting. The user interfaces for language setting and login. When inspector running the application, language setting interface is shown first. After select language, inspector login using his ID and password. The application request assessment list to database and show assessment list after login. The inspector add incident using plus button, and watch detail information of incident through click the list. Fig. 6, shows the interfaces to display incident list and detail information of incident. The inspector can get GPS information to add regional information to assessment. Fig. 7 shows interface for displaying map, general setting, and network setting. The inspectors can check network information of his device in network setting and change application setting. Fig. 8 shows the data exchange between server side

FIGURE 2. MERCI's interface controller classes.

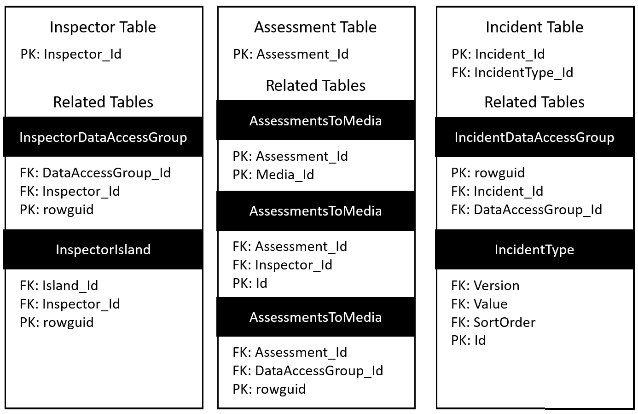


FIGURE 3. Database Structure of MERCI system.

Successful Authentication

```
Incoming JSON: {
    "authenticated": 1
}
```

Unsuccessful Authentication

```
Incoming JSON: {
    "authenticated": 0
}
```

FIGURE 4. The response of login request from server side application.

application and designed application, when user send login request message to server, postman application shows the data sent from server.

IV. THE PROPOSED MA-VFBC SCHEMES

A. MA-VFBC TECHNIQUES AND ROI ENVIRONMENT

This section buttresses the three novel path-tracking schemes as articulated and implemented in this work. They are named as the ''Follow-the-Carrot'', ''Pure-Pursuit'' and ''Follow-the-Past'' techniques. While there are evident resemblance between the ''Follow-the-Carrot'' and the ''Pure-Pursuit'' techniques which allows the sink node to utilize the deployed landmarks (beacons) to sense, discover,

```
Incoming JSON: {
    "total": {IncidentsTotal},
    "type": "DevicePosition",
    "results": [{
        "deviceid": "TrackingUser",
        "source": " ",
        "timestamp": "{TimeStamp}",
        "latitude": "{Latitude}",
        "longitude": "{Longitude}",
        "altitude": "0",
        "heading": "-1"
    }]
}
```

FIGURE 5. The JSON object to report positioning data.

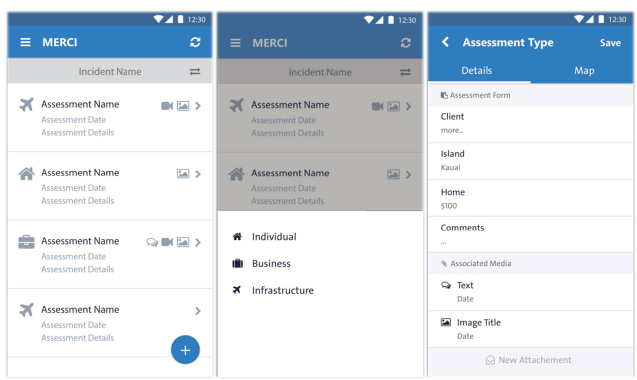


FIGURE 6. UI for Displaying Assessment (Left), Adding Assessment (Middle), Displaying Detail Assessment (Right).

fetch and process path information until the target node or goal is met, the ''Follow-the-Past'' however works differently by utilizing the existing/previous mapping information to track and locate the goal or target node.

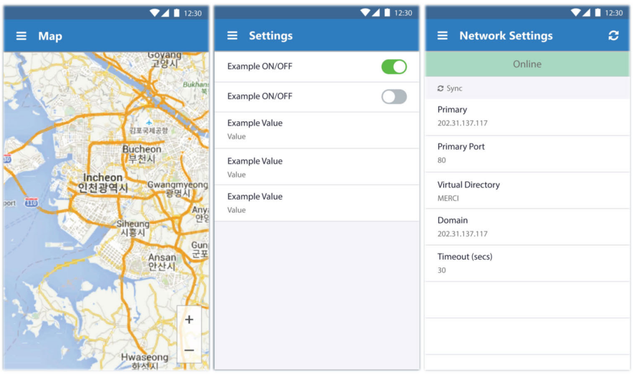


FIGURE 7. Displaying GPS Information (Left), General Setting (Middle), and Network Setting (Right).

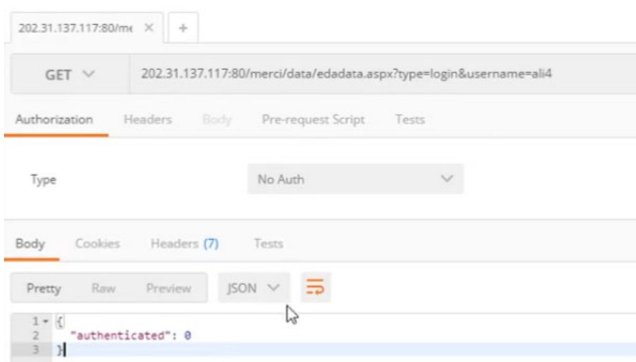


FIGURE 8. Data Response from Server Side Application.

The three proposed path-tracking techniques analyzes real time dissimilarities such as constraints in path-tracking distance, computation time to hit the goal, distances from the multiple but static obstacles, look ahead angle, goal angle and sensor node orientation. These were achieved with specified number of paths, signal to noise ratios (SNR), and travel velocity of sink node.

B. MATHEMATICAL MODEL AND FORMULATION

In this section, a sensor network with N-number of deployed scattered sensors $s_1, s_2, s_3, \ldots, s_N$ and with each one of the nodes confined to a communication range R_c and radius R_c, then their initial deployment is hinged upon the coverage mathematical expressions as presented by [38] which follows the basic principles:

- *Principle*1 : A connectivity graph $G = (V, E)$ is constructed where V depicts the vertices set that is controlled by the deployed mobile sensors with sensor edges E expressed as $E = (s_i, s_j)|\forall s_i, s_j \in V \wedge s_i \neq s_j \wedge d(s_i, s_j)$.
- *Principle*2 : The virtual nodes S and D are combined and the graph G is now re-constructed as thus: $G^* = (V^*, E^*)$, denoting the obstacle's boundaries from left to right boundary.
- *Principle*3 : The barrier coverage using the depth-first (DF) search approach in G^* is checked.

To calculate the probability of barrier coverage, thus:

$$P_r = \frac{RectangularArea_N}{IRDeployment_N}, \tag{1}$$

where $RectangularArea_N$ denotes the No. of times the rectangular area is barrier-covered and $IRDeployment_N$ is the Total number of initial random sensor deployments.

Since the sensor nodes s_i with coordinates (x_i, y_i) and neighbor nodes number N_i are all confined in same network communication zone R_c of s_i. Therefore, the net force in an X-direction is deduced as:

$$\vec{F}_{ix} = \sum_{i=l}^{N_i} \vec{F}_{ij}^{x} + \vec{F}_{iB}^{X}, \tag{2}$$

where F_{ij}^{x} implies the exerted force on w.r.t its neighbor node s_j, while F_{iB}^{X} denotes the total repulsive force of s_j as exerted by both boundary of X-coordinates X_1 and X_2 respectively.

The maximum number of sensors that can be deployed as formulated by Haque *et al.* in [39] is represented by:

$$max\,\{N|\,A_R\} = A - \sum_{i=l}^{m} O_i. \tag{3}$$

The above equation (1) considered a deployment of sensors at its maximum of NS_{max} given that the A has a dimension in length and breadth which are a multiple of S. In the event that the region is devoid of any obstacles, the N by K sensors can now be deployed such that $N = L/\Delta x$, and $K = W/\Delta y$, where O_i indicates the area of the i^{th} obstacle.

V. STRATEGIES FOR SINK NODE DEPLOYMENT, DETECTION AND TRACKING OF TARGET NODE

A. EMBEDDED PLC WITH SENSORS AND ACTUATORS

A reliable and guaranteed communication of sensors/actuators is achieved using both the nano and the micro varieties of the PLC device. The simplicity and reliability of the PLC device, coupled with its economical value are it preferable options for our works, as against other similar technologies. To achieve an optimal communication chain between the PLC and the Cloud storage devices, a dual field bus protocol is implemented. The PLC (server-side) gathers information as updated by the MERCI user assessment tool on the current location, through the deployed scattered sensors, actuators and other embedded data-gathering input/output devices, while the cloud server (client-side) processes these data w.r.t kind of expected output using an artificial neutral network algorithm called as re-current neutral network (RNN).

Mobile-based sensing/detecting devices such as industrial sensors and actuators are connected to the embedded input/output generator (PLC device). When data are sensed/detected by the sensors, actuator actions are triggered, hence ensuring that feedback reports are sent through dedicated channels to the cloud. The varieties of sensors in use here includes the atmospheric (gas and smoke) sensors such as the HVAC(heating, ventilation and air-conditioning). Other sensors used here are the soil moisture and water-level sensors such as the VH400. These sensors have wider

TABLE 1. Description of notations.

Notation	Definition
GUI	Graphical user interface
ROI	Region of interest
GPS	Global positioning system
KML	Keyhole markup language
JSON	JavaScript object notation
SQL	Structured query language
API	Application program interface
PLC	Programmable logic controller
CIR	Channel impulse response
TR	Transmitted response
CM	Code multiplexing
offset	A single step size
TR_{sensor}	Robots sensing range
oDir	Direction of obstacles
cp	Current position
co	Coordinate
ops	Operation type
BF	Boundary flag
mDir	Moving direction
goBack	Move back backward path

Algorithm 1 PLACESENSOR Techniques to Drop and Store Sensor Details at Sink's Current Position

Input: Maximum coordinates (maxP), Current position (cp), Current Robot Direction (mDir) and offset.
Output: Robot drops a sensor at its current position represented by (cpX) and (cpY).
PLACESENSOR (maxP, cp, mDir, offset)
cpX = cp[0] + offset;
cpY = cp[1] + offset;
maxX = 200, maxY = 200;
if *(cpX maxX) AND (cpY maxY)* **then**
  Drop sensor at (cpX, cpY)
  Store cpX, cpY, mDir in the robots memory
end

Algorithm 2 Initial Sensor Deployment With Mobile Processing Sink Node Device

Input: Start position (sp) and current position (cp).
Output: Target area covered by the robot.
offset $= TR_{sensor}$, $mDir = right$, $BF = 0$, $maxX = 200$, $maxY = 200$;
if *(oDir = NORTH)* **then**
  PLACESENSOR(maxY,cp,mDir,offset)
end
if *(oDir = SOUTH)* **then**
  PLACESENSOR(maxY,cp,mDir,-offset)
end
if *(oDir = EAST)* **then**
  PLACESENSOR(maxX,cp,mDir,offset)
end
if *(oDir = WEST)* **then**
  PLACESENSOR(maxX,cp,mDir,-offset)
end
if *(oDir = NORTH/SOUTH)* **then**
  co = Y
end
if *(oDir = WEST/EAST)* **then**
  co = X
end
if *(oDir = NORTH/EAST)* **then**
  ops = ≤
end
if *(oDir = WEST/SOUTH)* **then**
  ops = ≥
end
repeat
repeat
PLACESENSOR;
forward to mDir
until obstacle = 0 or BF = 0;
until cp.coopsmaxP.co;
goBack;
add offset;
BF = 0

coverage strength with long-lasting life cycle and are easily adaptable to other actuators and input/output devices.

A scalable technique to store and process details of the sink node's current position is depicted in the algorithm 1. The investigation here, known as the PLACESENSOR technique allows the robot to drop sensors at its current position after carefully obtaining information of its current position (cp), its maximum coordinates (maxP), robot's direction (mDir) and the offset. These sensors are then used as beacon to path-track the deployed sink node until the target node is reached. The PLACESENSOR nodes which is also referred to as the relay node proceeds to the initial sensor deployment phase in algorithm 2, once it is achieved. In algorithm 2, the initial sensor deployment technique using processing sink node device information is formulated. The entire ROI target area is covered until the target node is met. The sensor's start position (sp) and current position (cp) are obtained from the previous PLACESENSOR technique, while static obstacles in the line of sight of the robot's sink node are avoided using robot's direction (mDir) methodology.

The formulation of the relay sensor's received signal strength for the *ith* term, emanating from a source (S), and the end-to-end signal detection with broadcasting methodologies using the multiple input multiple output ultrawideband

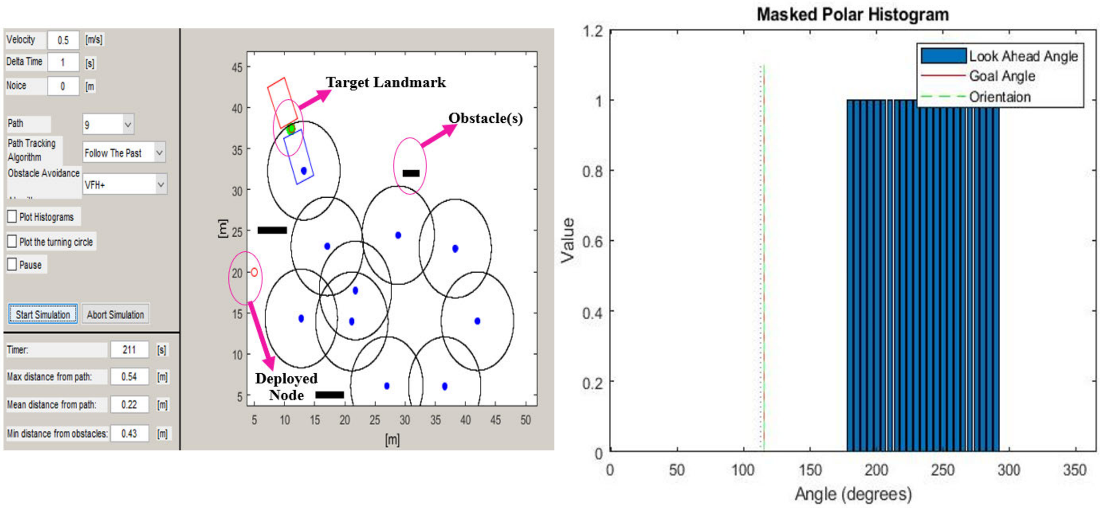


FIGURE 9. A "Follow-the-Past" path tracking algorithm with total path number placed at 9 and in the presence of multiple dissimilar obstacles. A total of 211 s computation time over a maximum path distance of 0.54 m was recorded.

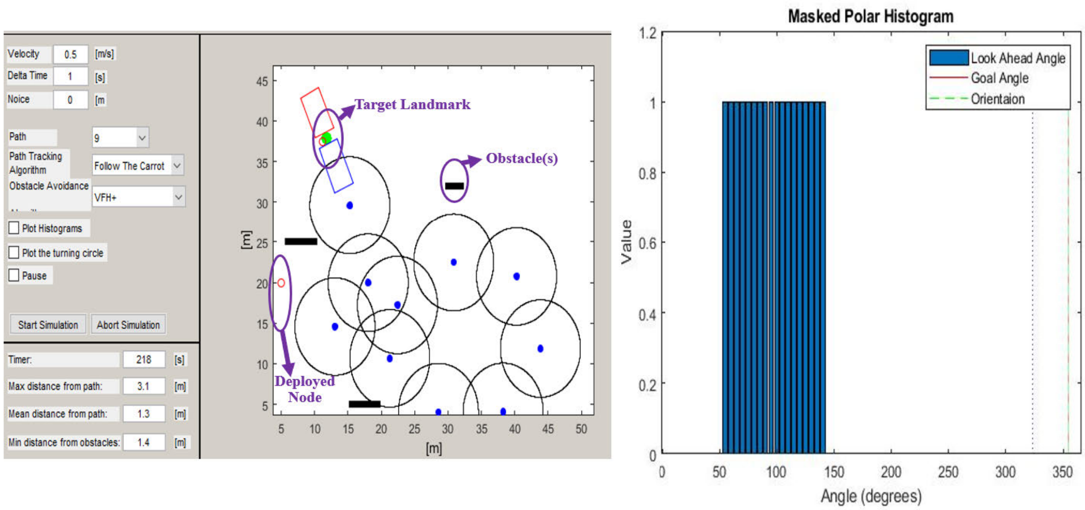


FIGURE 10. A "Follow-the-Carrot" path tracking algorithm with total path number placed at 9 and in the presence of multiple dissimilar obstacles. A total of 218 s computation time over a maximum path distance of 3.1 m was recorded.

(MIMO-UWB) Standardized network channels is presented as follows:

$$r(t) = \sum_{m=1}^{2}\sum_{j=0}^{N_f-1} \sqrt{E}_{p_m}(d_{i,m}\, c_j + \tilde{c}_{j,m}) \times g_m(t - iT_s - jT_f + n(t)), \quad (4)$$

where the input waveform $g_m(t) = p(t).h_m(t)$ refers to when the impulse $p(t)$ that is transmitted is appended to its consequent channel impulse response (CIR) $h_m(t)$ for the network link $T_m \longleftrightarrow R$, while the additive Gaussian noise with two-sided power spectral density is denoted by $n(t)$.

From the analysis as presented above, the decision variable for the same *ith* term can be computed as:

$$Z^{(\pm)} = \sum_{j=0}^{N_f-1} (c_j\tilde{c}_{j,1} \pm c_j\tilde{c}_{j,2}) \int_{t_{i,j}}^{t_{i,j}+T_I} [r(t)^2 dt], \quad (5)$$

The transmitted reference (TR), as derived from an optimal code multiplexing (CM) derivative is deduced here as:

$$s_R(t) = \sum_{j=0}^{N_f-1} \sqrt{E}_{p_R}(d_{i,R}\, c_j + \tilde{c}_{j,R})p(t - iT_s - jT_f). \quad (6)$$

VI. PERFORMANCE EVALUATION

A. SIMULATION RESULTS AND ANALYSIS

The results of the simulation depicts the scenarios after the deployment of the mobile sensors was achieved. In Fig. 9, depicts a "Follow-the-Past" path tracking algorithm with its path number placed at 9 and in the presence of multiple dissimilar obstacles. A total of 211 s computation time over a maximum path distance of 0.54 m was recorded. Fig. 10 presents a "Follow-the-Carrot" path tracking algorithm with its path number placed at 9 and in the presence of multiple dissimilar obstacles. A total of 218 s computation time over a maximum path distance of 3.1 m was recorded. For Fig. 11, a "Pure-Pursuit" path-tracking algorithm with its path number placed at 9 and in the presence of multiple

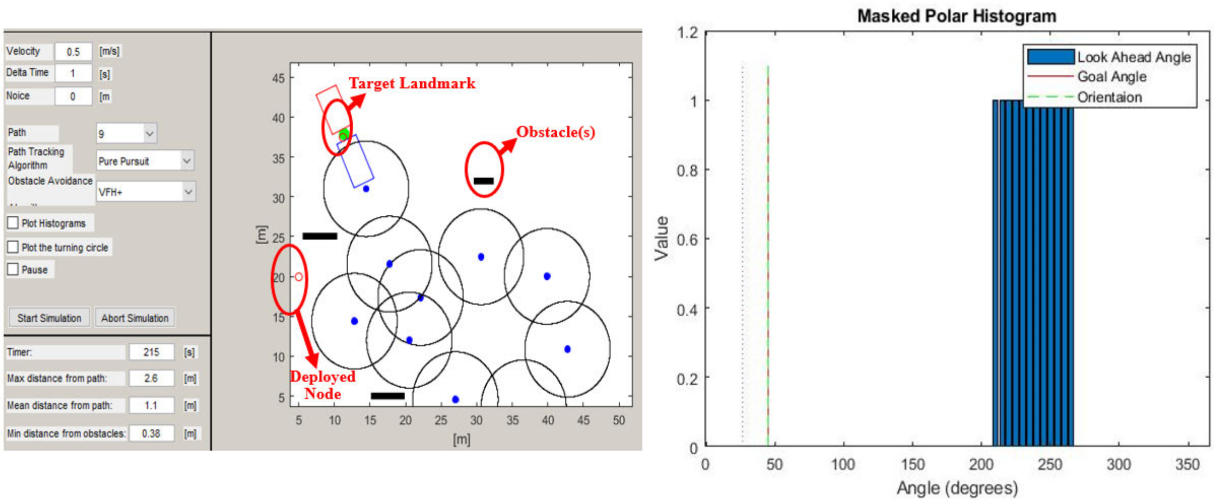
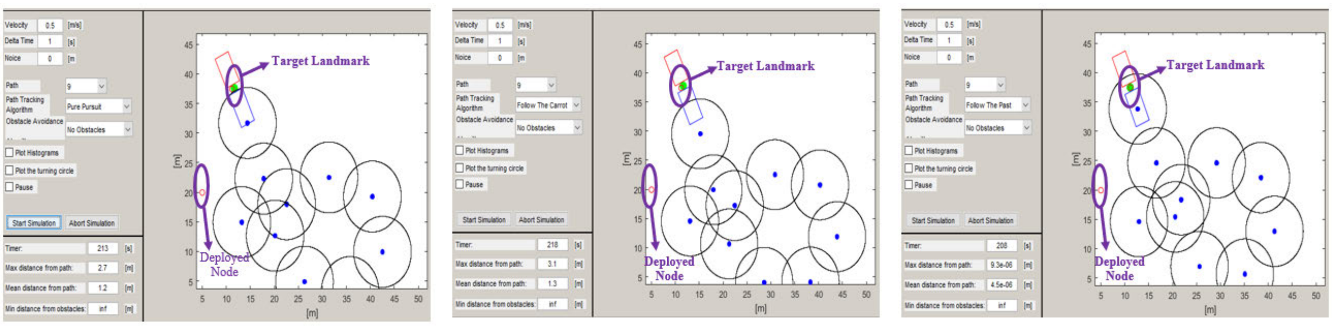


FIGURE 11. A "Pure-Pursuit" path-tracking algorithm with total path number placed at 9 and in the presence of multiple dissimilar obstacles. A total of 215 s computation time over a maximum path distance of 2.6 m was recorded.

TABLE 2. Summary of the MA-VFBC Techniques with Three Dissimilar-shaped Static Obstacles.

MA-VFBC Technique	Path Nos.	Computation Time (S)	Max. & Mean Distance from Path (M)	Min. Distance from Obstacles (M)
Follow-the-Past	9.0	211.0	0.54 & 0.22	0.43
Follow-the-Carrot	9.0	218.0	3.10 & 1.30	1.40
Pure-Pursuit	9.0	215.0	2.60 & 1.10	0.38



(a) (b) (c)

FIGURE 12. (a). Implements the "Pure-Pursuit" scheme, where its path number is placed at 9 while a total of 213 s computation time over a maximum path distance of 2.70 m is recorded. (b). Implements the "Follow-the-Carrot" scheme, where its path number is placed at 9 while a total of 218 s computation time over a maximum path distance of 3.10 m is recorded. (c). Implements the "Follow-the-Past" scheme, where its path number is placed at 9 while a total of 208 s computation time over a maximum path distance of 9.3e-06 m is recorded.

dissimilar obstacles was presented. A total of 215 s computation time over a maximum path distance of 2.6 m was recorded. The summary of Fig. 9, Fig. 10 and Fig. 1 are shown in Table 2.

The Fig. 12, which is categorized into (a), (b), (c), however differs from the other previously represented figures as the sensors were deployed and observations in an environment with no obstacles at all. The summary of Fig. 12 is presented in Table 3. While Fig. 12(a), using the "Pure-Pursuit" scheme, where its path number is placed at 9 while a total of 213 s computation time over a maximum path distance of 2.7 m is recorded, and Fig. 12(b) using the "Follow-the-Carrot" scheme, where its path number is placed at 9 while a total of 218 s computation time over a maximum path distance of 3.1 m is recorded. Fig. 12(c) implements the "Follow-the-Past" scheme, where its path number is placed at 9 while a total of 208 s computation time over a maximum path distance of 9.3e-06 m is recorded.

TABLE 3. Summary of the MA-VFBC Techniques without Obstacles.

MA-VFBC Technique	Path Nos.	Computation Time (S)	Max. & Mean Distance from Path (M)
Follow-the-Past	9.0	213.0	2.70 & 1.20
Follow-the-Carrot	9.0	218.0	3.10 & 1.30
Pure-Pursuit	9.0	208.0	9.3 e-06 & 4.5 e-06

The simulation results showed the validation of the proposed MA-VFBC based approaches and demonstrated the effectiveness of the scheme w.r.t real-time reliability issues that were considered. It also showed the promising strategies for the scheme's deployment in other system sphere other than a Region-of-interest (ROI) location.

VII. CONCLUSION

A real-time deployment of mobility sensors, targeted for a region of interest (ROI) or in unsafe environment was investigated in this paper. The prerequisite to obtaining real-time values necessitated the proposal of three novel, but dissimilar mobile and adaptive virtual force barrier coverage (MA-VFBC) based path-tracking models for our sensor deployment. Thorough simulation demonstration of the effectiveness of the MA-VFBC based model techniques was presented in the following aspects: (a). The investigations was modeled using deterministic probability models for the path-tracking, where sensing and communication ranges of the nodes are in circular disk. (b). The current research works complimented the probabilistic communication and sensing models as better candidates for accurate representation of reality. (c). Since a relative neighborhood graphing scheme was used to communicate with the sensor nodes, the minimal energy consumption variance was observed as all nodes are idle unless awoken by a neighbor node. Future work will focus at enhancing the system's flexibility to multi-interact with other remotely positioned systems. The need to also maintain a low installation/deployment cost that is capable of running a wireless sensor network and powered for other target systems, thereby addressing the probabilistic communication and sensing models will be investigated.

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