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RESEARCH ARTICLE

A Multi-Objective Situational Awareness Approach for Distribution Networks Using Drones

HAIAM SHAHIN[1], MOSTAFA F. SHAABAN[2], (Senior Member, IEEE), MAHMOUD H. ISMAIL[2,3], (Senior Member, IEEE), HEBAT-ALLAH M. MOURAD[3], AND AHMED KHATTAB[3], (Senior Member, IEEE)

[1]Arab Academy for Science, Technology and Marine Transportation, Khorfakkan Branch, Khorfakkan, United Arab Emirates
[2]Department of Electrical Engineering, American University of Sharjah, Sharjah, United Arab Emirates
[3]Department of Electronics and Communications Engineering, Faculty of Engineering, Cairo University, Giza 12613, Egypt

Corresponding author: Mostafa F. Shaaban (mshaaban@aus.edu)

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ABSTRACT Unmanned aerial vehicles (drones) have gained a high level of practical confidence due to their ease of use in different applications as well as their advantages such as flexibility, ease of operation and low cost. In this paper, we propose the use of drones equipped with onboard sensors for monitoring the status of electrical distribution networks. Specifically, we formulate a multi-objective optimization approach for distribution networks' situational awareness, which aims to minimize two conflicting objectives. These are the total annual cost and loss of observability. The proposed approach decides on the optimal number of drones, their batteries, the nodes to be visited, and the trip plan. In order to obtain a set of Pareto solutions, we utilize the non-dominated sorting genetic algorithm (NDSGA) in conjunction with branch-and-bound algorithm to minimize both objectives. To validate the performance of the proposed approach, we applied it to a practical distribution system under different scenarios of monitoring frequency and working hours. The obtained results prove the effectiveness of the proposed approach.

INDEX TERMS Distribution network, drones, power source sizing, trip planning, observability, non-dominated sorting genetic algorithms.

I. INTRODUCTION

Distribution networks status monitoring is very important for electric power utilities to ensure reliability, customer satisfaction, and operating cost reduction. It is estimated that utilities in the US lose up to 3.5% of their annual revenue due to electricity theft [1]. Therefore, it is crucial to monitor the network continuously. Although the transmission system is usually fully monitored, it is only possible to partially monitor the distribution one. This is because it is financially infeasible to fully monitor it due to the associated large number of nodes and lines when compared to the transmission system. In fact, some distribution systems have as low as only 0.1% of their nodes monitored.

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The status of the distribution system is monitored by installing Supervisory Control and Data Acquisition (SCADA) metering devices. As mentioned earlier, monitoring all nodes is very expensive and only a few SCADA units are installed on certain limited nodes in the system. Consequently, the loss of system observability (the ability to observe the power lines voltages, currents, and powers) is inevitable. These nodes need to be carefully selected to maximize the observability of the system as much as possible and to monitor different parts of the system [2], [3]. Although some standards are available for the communication and cybersecurity requirements in substations, such as IEC 61850 [4], there are no similar ones for the required suitable number of monitoring devices in distribution systems nor for their placement. Hence, several approaches were proposed in the literature to optimally position these devices as in [5], for example.

To address the main challenge of monitoring the distribution networks at a proper observability level with minimum budget, we propose using drones equipped with sensors for monitoring several locations at different periods of time. The monitoring can be done by hooking sensors temporarily to the line to allow measuring the voltages and currents. Thus, there is no need to place a metering unit at each bus. However, the drawback of the proposed solution is that monitoring is for a short period of time and not simultaneously at different buses. In spite of that, this could be satisfactory for distribution systems operators to know the status of the system during peak demand hours, which is the most critical period of the day. This will help in identifying information related to system reliability, power quality, and electricity theft, which we will call situational awareness.

More specifically, in this paper, we present a new multi-objective optimization framework to optimize the number of drones and their battery sizes needed for monitoring distribution networks. The proposed framework also determines their optimal charging locations, trip planning, and the number of buses that have to be visited, as well as their locations. It is worth mentioning that the proposed work can only be applied to rural and sub-urban systems with overhead lines due to the nature of the sensing process involved. In addition, the proposed methodology requires steady hovering, which can only be performed using multi-rotor drones, such as quadcopters. The objectives of the proposed framework are the total annual cost and the loss of observability, which are simultaneously minimized to create a set of Pareto optimal solutions, which the distribution network operator can choose from.

The contributions of this work can thus be summarized as follows:

- Formulating a multi-objective optimization problem to minimize two conflicting objectives, namely the cost and the loss of observability in the system using a non-dominating sorting genetic algorithm (NDSGA-II).
- Proposing a new drone-based approach for monitoring the distribution networks by solving the formulated problem.
- Two different cases are studied taking into consideration the effect of observing recurrence and the effect of the number of daily working hours.
- Validating the performance of the proposed framework using an extensive set of experiments using the data of a practical distribution system.

The rest of this paper is organized as follows. An overview of related work is presented in Section II. The system model is discussed in Section III. In Section IV, we present the multi-objective problem formulation aiming at simultaneously minimizing the total annual cost for all trips and the loss of observability. In Section V, we present the proposed joint algorithm for solving our problem. Simulation results are then presented in Section VI. The paper is finally concluded in Section VII.

II. RELATED WORK

In this section, we review the most relevant works in the literature related to monitoring power lines. The first set of works addresses optimizing the locations of monitoring units to achieve multiple goals. For example, an allocation model for monitoring distribution systems where non-technical losses are the main reason for voltage sags was suggested in [6] based on the P-median model. After obtaining the monitors' optimal locations, the modified P-median model was enforced to obtain complete observability in the system. Also, in [7], genetic algorithms and fuzzy set programming were applied in different types of short circuits to solve the allocation problem of power quality monitors to detect the occurrence of voltage sags and swells. Similar to the above works, the authors of [8] suggested a branch-and-bound programming algorithm to optimize the locations of power quality meters, which were used to monitor the voltage sags in a large transmission system. Along the same lines, the work in [9] minimized the number of necessary measuring devices and optimized their locations in a process based on correlation and regression analysis of simulated measurements time series. In [10], the authors optimized the location of meters while guaranteeing the observability of the system in the case of possible single emergency and loss of single measurements. An allocation scheme that aims at finding the minimum number of locations of the monitoring equipment was suggested in [11] to maximize a detection capability index. The problem formulation is based on characterizing the system in terms of the most likely short circuits that could occur in the system and was solved by using Genetic Algorithms (GA). The work in [12] optimized the power quality monitors (PQM) and considered both the fault location and the observability of the system constraints. The authors suggested a local search algorithm to solve the problem. Also, the authors in [13] proposed a methodology based on Kirchhoff's current and voltage laws and the branch-and-bound algorithm to optimize the location of power quality meters in the IEEE 14-bus system while achieving maximum observability.

The second set of works addresses cost minimization by optimizing the monitoring devices locations. In particular, an approach for allocating monitoring devices was studied in [14] to minimize the total cost while guaranteeing total observability. The problem was formulated using binary integer programming and solved by applying the branch-and-bound method. Moreover, the total cost of the monitoring system was minimized by optimizing the number and locations of monitoring devices with observability constraints in [15]. Integer programming was used for solving the proposed optimization problem and the formulation of the constraints did not require any knowledge about generation or loads in the system. Also, an integer linear programming algorithm was proposed in [16] for reducing the cost of the distributed monitoring system with data redundancy constraints by optimizing monitors allocations. Furthermore, the monitoring system cost was minimized in [17] by optimizing the number of power quality monitors. Also, an optimization allocation problem of power quality monitors was formulated in [18] as a non-linear integer problem for minimizing the total cost while maximizing the redundancy of measurements. The optimization problem was solved by compact genetic algorithm (CGA). The branch-and-bound method was suggested to minimize the total annual cost and guarantee total observability in the Brazilian Electrical Transmission and Distribution Systems in [14]. The work in [19] formulated the optimum allocation problem of transmission systems monitors as a multi-objective problem to acquire the lowest cost solution with the highest data redundancy. The formulated problem was solved by using an extended compact genetic algorithm.

The third set of works focus on the use of drones to establish monitoring systems. Lots of works in the literature have already inspected this idea but in different applications. For example, the work in [20] collected all information about using drones outfitted with sensors in the field of chemical sensing. Also, the authors in [21] studied the use of drones for sensing the traffic speed, ozone, carbon dioxide, temperature, and humidity levels.

Since the proposed framework in this paper is based on multi-objective optimization, we now focus on works in the literature that tackled similar frameworks and discuss how the problem was solved. In particular, the authors in [22] combined differential evolution (DE) with particle swarm optimization (PSO) algorithm in a hybrid multi-objective algorithm with no guarantee of the closeness of this solution to the true Pareto-Optimal frontier. Also, in [23], the authors suggested the use of the non-dominating sorting genetic algorithm (NDSGA). An adjusted version of an effective ant colony optimization (ACO) was proposed in [24] for solving a multi-objective resource allocation problem. Finally, a multi-objective evolutionary algorithm (MOEA) was combined with the multi-objective computing budget allocation (MOCBA) method to optimize a multi-objective aircraft spare parts allocation problem in [25].

As the main goal of this work is to increase system observability at a minimum cost, we propose a multi-objective genetic algorithm to get a set of Pareto optimal solutions for minimizing the total annual cost and the loss of observability. In particular, the number of drones, their proper batteries, starting points, which also act as their charging pad locations, and trip planning are jointly optimized as will be detailed in the sequel.

III. SYSTEM MODEL

We consider a system with $d \in \mathcal{U} = \{1, 2, \ldots, U\}$ multi-rotor drones equipped with sensors for monitoring the overhead lines, where U is the maximum number of available drones, and there is a set of batteries $\mathcal{B} = \{1, 2, \ldots, B\}$ from which each drone is assigned only one. The power distribution system has N buses that are labelled according to the set $\mathcal{N} = \{1, 2, \ldots, N\}$. Let $C_{i,j,p}$ represent a binary variable that indicates whether or not a connection between bus $i \in \mathcal{N}$ and bus $j \in \mathcal{N}$ for phase p exists. For $i = j$, $C_{i,j,p} = 1$, and for $i \neq j$, if there is a connection between buses i and j; then, $C_{i,j,p} = 1$, otherwise, $C_{i,j,p} = 0$. Also, let the coordinates of the n^{th} bus be denoted by $\boldsymbol{q}_n \in R^{2\times 1}$. Now, each bus $i \in \mathcal{N}$ has a number of connections n_i given by

$$n_i = \sum_{j \neq i} \sum_{p \in P} C_{i,j,p}, \forall i \in \mathcal{N}, \tag{1}$$

where $\mathcal{P} = \{1, 2, 3\}$ is the set of phases. The system lines are monitored in a number of trips T, where $T \leq N$. Moreover, we assume that each bus should be visited once during the monitoring period $\mathcal{T}$, and the drone hovers over each connection of the bus for a certain time t_h to monitor the overhead connections. Consequently, the drone's hovering time T_i^{sens} over bus i is simply given by

$$T_i^{sens} = t_h n_i. \tag{2}$$

Also, let the starting point of the d^{th} drone be denoted by g_d, which is assumed to have coordinates $\boldsymbol{q}_{g_d} \in R^{2\times 1}$. Finally, we define the subset of buses visited by drone d as $\mathcal{N}_d = \mathcal{N} \cup \{g_d\}$.

The number of trips for each drone will clearly depend on the available charge in the drone's battery, the distance between buses, the number of connections to each bus, and the number of buses. In the following, we elaborate on the two conflicting objectives that will be tackled in the multi-objective optimization formulation.

A. SYSTEM OBSERVABILITY

Various degrees of system observability can be achieved depending on the location where the drone hovers for monitoring a certain bus. One of the greatest challenges that face the system designers is obtaining 100% system observability. Based on that, observability is defined as the percentage of the fully observed states in the system [26], i.e.,

$$\frac{\sum_{s \in \mathcal{S}} W_s}{O} \times 100\%, \tag{3}$$

where $\mathcal{S} = \{1, 2, \ldots, O\}$ is the set of all possible observable states, O represents the total number of observable states and W_s represents a binary variable that indicates whether or not state $s \in S$ is observed. For an unbalanced system, the phase voltages at each bus and the phase currents in the lines connected to the bus are considered as separate states because each bus may not have all three phases connected. Hence, the total number of observable states is calculated as follows:

$$O = O^I + O^V, \tag{4}$$

where O^I and O^V are the number of current and voltage observable states, respectively. We define $\mathcal{S}^V, \mathcal{S}^I \subset \mathcal{S}$ as the subsets of voltage and current states, respectively. It is worth mentioning that there are up to 3 voltage states in each bus, and up to 3 observable current states between every two connected buses.

In an unbalanced system, some buses may not have all the three phases, so for any bus i in an unbalanced system, the three elements $C_{i,j,p}, \forall i = j, p \in \mathcal{P}$ do not have to be all ones. Hence, the number of voltage states O^V is calculated as follows

$$O^V = \sum\nolimits_{i\in\mathcal{N}} \sum\nolimits_{p\in\mathcal{P}} C_{i,j,p}, \tag{5}$$

and the number of the current states O^I is calculated by finding the difference between the sum of all connections and O^V then multiplying the result by 0.5, i.e.,

$$O^I = \frac{\left(\sum_{i\in\mathcal{N}} \sum_{j\in\mathcal{N}} \sum_{p\in\mathcal{P}} C_{i,j,p} - O^V\right)}{2}. \tag{6}$$

Ohm's Law and Kirchhoff's Current Law (KCL) can be used to find the relationships between the nodes and the observability [16]. In particular, if the voltage and current are known at a certain end of one connection, the voltage at another end of this connection can be calculated. It is worth mentioning that the observability variable in (3) is calculated as

$$W_i = \min\left(W_i^{CN}, 1\right), \forall s \in \mathcal{S}, \tag{7}$$

where the number 1 indicates that the binary observability variable is set to 1 for any value more than 1, as redundancy in readings should not be considered and W_i^{CN} is a simple observability variable calculated as follows:

$$W_i^{CN} = A_{s,i} \times Z_i, \tag{8}$$

where $Z_i \in \{0, 1\}, \forall i \in N$ with $Z_i = 1$ indicating that bus i is visited by a drone and $Z_i = 0$ otherwise, and $A_{s,i}$ is the connectivity parameter of the system calculated by leveraging Ohm's law, which states that if the voltage and current at a certain bus are observable, the voltages at the other buses connected to this bus are also observable. Also, if the voltages at two buses are observable, the current flowing between them is observable too.

B. OVERALL COST

The cost associated with the considered system is that of the initial investment, which is assumed to be paid annually in addition to the operating cost of all trips per year. The former is basically the sum of the annualized capital cost of the drones and their associated wireless charging pads as well as their batteries while the latter represents the expenditures related to the consumed energy in flying and hovering a drone. The details of the costs are explained in the next section along with the problem formulation.

IV. PROBLEM FORMULATION

As mentioned earlier, the goal in this paper is to minimize the total annual cost denoted by f_1 of using drones for monitoring (including both the capital cost of the chosen set of drones and their associated batteries in addition to the operating cost of all the trips per year due to the drones' batteries recharging) as well as to minimize the loss of observability denoted by f_2, simultaneously. This is achieved via the proper choice of the number of drones, their batteries as well as proper choice of the drones' starting points and trip planning, in addition to finding the optimal number of buses to be visited by the drone and their locations. The optimization problem thus submits as a multi-objective optimal allocation approach, where the problem formulation can be defined as:

$$\left.\begin{aligned} &\min_{\mathcal{X},\mathcal{Y},\mathcal{Z},\mathcal{G}} (f_1, f_2) \\ f_1 &= \sum_{d\in\mathcal{U}} X_d \left(\text{cost}_d + \sum_{b\in\mathcal{B}} Y_{b,d}\left(\text{cost}_b + C_{b,d}^{total}\right)\right) \\ f_2 &= \left(1 - \frac{\sum_{s\in\mathcal{S}} W_i}{O}\right) \times 100\% \end{aligned}\right\} \tag{9}$$

where $X_d, d \in \mathcal{U}$ represents a binary decision variable that indicates whether or not drone d is selected and $\mathcal{X} = \{X_1, X_2, \ldots, X_U\}$. Also, $Y_{b,d}, b \in \mathcal{B}, d \in \mathcal{U}$ represents a binary decision variable that indicates whether battery b is associated with drone d and $\mathcal{Y} = \{Y_{1,d}, Y_{2,d}, \ldots, Y_{B,U}$. Moreover, $\mathcal{Z} = \left\{Z_{i,j,t,d}\right\}$, where $i, j \in \mathcal{N}_d \subset \mathcal{N}, t \in \mathcal{T} = \{1, 2, \ldots, T\}$, $d \in \mathcal{U}$ with $Z_{i,j,t,d} \in \{0, 1\}$ being another binary decision variable, which indicates that drone d travels from bus i to j as part of trip t. Finally, G represents the set of all candidate locations of the buses, which could act as possible starting points for any drone.

In (9), cost_d and cost_b are the annualized capital cost of the dth drone and the bth battery, respectively. The first is calculated as follows:

$$\text{cost}_d = \left(\frac{r\,(1+\text{r})^{L_d^{year}}}{(1+\text{r})^{L_d^{year}} - 1}\right) \times pr_d, \tag{10}$$

where pr_d and the quantity inside the parentheses represent the price and the capital recovery factor (CRF) of drone d and its associated wireless charging pad, respectively. The CRF converts the capital cost to annual payments at a discount rate r, where L_d^{year} is the lifetime of drone d in years [27]. The annualized capital cost of the battery $cost_b$ can be calculated as in (10) but using pr_b instead of pr_d and $L_{b,d}^{year}$ instead of L_d^{year} as the battery has a shorter lifetime (that depends on the number of charging cycles) compared to the drone. In addition, the lifetime of battery b when associated with drone d in years, $L_{b,d}^{year}$, can be calculated as:

$$L_{b,d}^{year} = \min\left(\frac{L_b^{cycle}}{C_{b,d}^{cycle}}, L_{max}\right), \tag{11}$$

where L_{max} is the chemical lifetime of any battery in years, which is independent of the number of recharging cycles and L_b^{cycle} represents the maximum number of recharging cycles of battery b (the battery discharges during each trip and needs to recharge afterwards). Finally, $C_{b,d}^{cycle}$ is the number of recharging cycles of battery b when associated with drone d per year, which, in turn, is given by

$$C_{b,d}^{cycle} = \frac{E_{b,d}^{year}}{\epsilon \times E_b^{max}}, \tag{12}$$

where the denominator term in (12) represents the actual useful energy of a battery with ϵ being the maximum depth of discharge and $E_b^{max} = C_b \times V_b$, is the battery capacity (in Wh) where V_b is its voltage rating and C_b is its capacity in Ah. Furthermore, $E_{b,d}^{year}$ is the consumed energy per one year (in Wh), and is calculated as follows:

$$E_{b,d}^{year} = \omega \times E_{b,d}^{mon}, \tag{13}$$

where ω is the frequency of the monitoring, and $E_{b,d}^{mon}$ is the consumed energy per one cycle by drone d when battery b is associated with it.

Also, in (9), $C_{b,d}^{total}$ is the annual operating cost per all trips when battery b is associated with drone d is equal to the battery charging cost, and is calculated as follows:

$$C_{b,d}^{total} = \mu \times E_{b,d}^{charg}, \tag{14}$$

where $E_{b,d}^{charg} = \frac{E_{b,d}^{year}}{\varphi}$ is the consumed charging energy, μ is the price per Wh in dollars and φ is the discharging/charging efficiency. Now, we are ready to describe the different constraints needed to complete the formulation of the optimization problem in (9).

A. TRIP PLANNING CONSTRAINTS

For any drone d and for any bus i that is visited in trip t, the total number of all outgoing trips to any other point needs to be equal 1. In addition, for any bus j, it is necessary to ensure that each point is visited only once in all trips and is visited by only one drone, so the total number of incoming trips from any other point needs to be equal to 1. These constraints can be formulated, respectively, as

$$\sum_{j\in\mathcal{N}_d} Z_{i,j,t,d} = 1, \forall i \neq g_d, \forall t, \forall d, \tag{15}$$

$$\sum_{i\in\mathcal{N}_d} Z_{i,j,t,d} = 1, \forall j \neq g_d, \forall t, \forall d. \tag{16}$$

It is important to note, however, that the constraints in (15) and (16) do not apply to the starting point $g_d \in \mathcal{G}$ of any drone d. Also, since every feasible solution must contain only one closed sequence of visited points so, in each trip t, the starting point g_d for the dth drone needs to have only one outgoing and only one ingoing connections. This is represented by the following two constraints:

$$\sum_{i\in\mathcal{N}}^{N} Z_{i,g_d,t,d} = 1, \forall t, \forall d, \tag{17}$$

$$\sum_{j\in\mathcal{N}}^{N} Z_{g_d,j,t,d} = 1, \forall t, \forall d. \tag{18}$$

Now, based on the above definitions, the total flying time for drone d during trip t is equal to

$$T_{t,d}^{flying} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} \left\| \mathbf{q}_i - \mathbf{q}_j \right\| Z_{i,j,t,d}}{V_d^{fwd}}, \forall i, j \in \mathcal{N}_d, \tag{19}$$

where V_d^{fwd} is the speed of drone d in the horizontal motion between any two buses in km/h and $\left\| \mathbf{q}_i - \mathbf{q}_j \right\|$ is the distance between buses i and j in km with $\|\cdot\|$ denoting the Euclidean distance. Furthermore, the total hovering time of drone d during trip t is equal to the summation of all hovering times during this trip, i.e.,

$$T_{t,d}^{sens} = \left(\sum_{i\in\mathcal{N}_d} \sum_{j\in\mathcal{N}_d} Z_{i,j,t,d} \right) T^{sens}, \forall t, \forall d, \tag{20}$$

where the quantity inside the parentheses represents the total number of buses visited in trip t by drone d. Finally, the drone does not work all day, but it works only for a certain time because it needs charging, and the city municipality might have limitations on drones' operation. This is in addition to the fact that the utility has specific working hours. Hence, one needs to add the following constraint:

$$T_{t,d}^{flying} + T_{t,d}^{sens} \leq \tau_d, \forall d, \forall t, \tag{21}$$

where τ_d is the maximum number of working hours for the drone.

B. NUMBER OF DRONES AND THEIR POWER SOURCE SIZING CONSTRAINTS

Clearly, the battery selected by any drone must have enough energy to enable the drone to cover the distance between its starting point and the furthest point in the transmission line because only one battery will be associated with each drone. This clearly leads to the following two constraints:

$$\sum_{b\in\mathcal{B}} Y_{b,d} = X_d, \forall d. \tag{22}$$

$$\sum_{b\in\mathcal{B}} Y_{b,d} l_b^d \geq 2 l_{g_d,n}, \forall n \in \mathcal{N}, \forall d, \tag{23}$$

where l_b^d is the maximum distance covered by drone d when equipped with battery b, $l_{g,n}^d$ is the distance between the starting point of drone d and any bus n that needs to be visited, and the factor 2 is included to ensure that the drone can come back again to its starting point for recharging after finishing its trip.

Next, since the discharge power limit of the drone's battery should be greater than the maximum consumed power of the battery during either hovering and power quality monitoring or forward motion, the following constraint needs to be included:

$$\sum_{b\in\mathcal{B}} Y_{b,d} P_b^{\max} \geq max\left(P_{b,d}^{consumed}\right), \quad \forall d, \tag{24}$$

where $P_b^{\max} = E_b^{max} \times C_b^{rate}$, is the maximum discharge of battery b, and C_b^{rate} is the C-rate of battery b in h^{-1}. On the other hand, $P_{b,d}^{consumed}$ is the power consumed during the hovering or flying of drone d when powered by battery b

and is calculated as:

$$P_{b,d}^{Hovering} = \left(m_{0,d} + \sum_{b} Y_{b,d} m_b\right) g \sqrt{\frac{2m_d^{tot}}{n_d A_d \rho}} \quad (25)$$

$$P_{b,d}^{Flying} = \frac{1}{2} \rho n_d A_d v_{air} \left(v_{air}^2 - v_{f,d}^2 \sin \theta_d^2\right) \quad (26)$$

where $m_{0,d}$ is the dead mass of the drone d, m_b is the mass of battery b, g is the gravitational acceleration, ρ is the air density, n_d is the number of rotors in the drone, v_{air} is the velocity of air, A_d is the area of the cylindrical mass of air, which represents the force created by the motion of the blades of drone d, $v_{f,d}$ is the drone forwarding flight velocity and θ_d is its tilt angle. It is worth noting that the consumed power during flying is constant for drone d.

Next, the useful energy of the battery must be enough to cover each trip by drone d assuming the battery is recharged between trips. Hence,

$$\sum_{b} Y_{b,d} E_b^{useful} \geq \left(E_{t,d}^{flying} + E_{t,b,d}^{sens}\right), \forall t, \forall d \quad (27)$$

where $E_{t,d}^{flying}$ and $E_{t,b,d}^{sens}$ are the consumed energies by drone d during the forward motion and while hovering in trip t, respectively and are calculated as:

$$E_{t,d}^{flying} = P_{b,d}^{Flying} \times T_{t,d}^{flying}, \forall t, \forall d, \quad (28)$$

$$E_{t,b,d}^{sens} = P_{b,d}^{Hovering} \times T_{t,d}^{sens}, \forall t, \forall d, \forall b. \quad (29)$$

Finally, it is important to note that the total consumed energy during all trips needs to be equal to the sum of the consumed energies during hovering and during flying motion in all trips, which for drone d is given by

$$E_{b,d}^{monitoring} = \sum_{t} E_{t,d}^{flying} + \sum_{t} E_{t,b,d}^{sens}, \forall d, \forall b \quad (30)$$

$E_{b,d}^{monitoring}$ can be calculated by substitution from (28) and (29) into (30).

V. PROPOSED SOLUTION APPROACH

In order to solve the previously introduced multi-objective optimal allocation problem (9), which is a mixed integer non-linear program (MINLP), we propose using the non-dominated sorting genetic algorithm (NDSGA-II) as detailed in the flow chart in Fig. 1. The most important advantage of the proposed method is that NSGA-II simultaneously optimizes each objective. Also, NSGA is a popular and fast-sorting multi-objective genetic algorithm, which can handle non-penalty constraints. It enjoys a fast and efficient convergence. It is also capable of searching on a large scale and dealing with problems that start with a non-feasible solution.

The proposed algorithm is based on several layers of classifications of the individuals where non-dominated individuals get a certain dummy fitness value and then are removed from the population. The process is repeated until the entire population has been classified. NDSGA-II has advantages such as introducing elitism to NDSGA besides diversity preservation in a fast and less complex algorithm [28].

In more details, NDSGA-II selects the optimal number of drones, their proper battery sizes, their proper charging point (starting point), and the assigned buses to each drone. Furthermore, the algorithm assigns these buses to trips, the optimal number of buses to be monitored, and their locations. All of the previous selections are then passed to the fitness calculation of NDSGA, which has two parts. The first part is responsible for calculating the loss of observability (objective one), and it receives its input as the number of buses to be monitored and their locations. The second part is responsible for calculating the total annual cost (objective two), which receives its inputs as the selection of the number of drones, their proper battery sizes, their proper charging point (starting point), and the assigned buses to each drone.

Inside the second part, there is an internal sub-problem to obtain the optimum route for each trip. This internal sub-problem is comparable to the travelling salesman problem (TSP) [29], which is solved using the branch-and-bound method that yields a good solution in a reasonable time. After calculating the optimal route for each trip, NDSGA uses the selected route and the specification of the selected battery to check the constraints for each trip, i.e., the maximum of hovering and flying power must be less than or equal to the selected battery's power consumption as in (24). Furthermore, the consumed energy must be less than or equal to the actual useful energy of the battery, as in (27).

VI. SIMULATION RESULTS AND DISCUSSIONS

In this section, we provide simulation results to demonstrate the performance of the proposed approach. Table 1 summarizes the simulation parameters used to produce our results. We used a distribution network for a utility in the US provided by the Electric Power Research Institute (EPRI-Ckt5) [30], which is a 76.4552 km unbalanced system with 973 buses as shown in Fig. 2 [31]. We assume that the drones have no contact with the wires, and the current is calculated by sensing the magnetic field emitted by the wires as in [32]. Also, for voltage sensing, a contactless approach such as in [33] can be used, otherwise, the drone must be able to deploy a probe to the conductor.

Concerning the candidate drones, we assume a set of 19 identical drones whose specifications are summarized in Table 1. Also, a set of 19 batteries whose specifications are summarized in Table 2 are used. The results in this work will be given in terms of the Pareto frontier where every point in the frontier represents the two objectives (total annual cost and loss of observability) and the associated optimal number of drones, their batteries, their starting points, and the trip plan for each drone. MATLAB was used to generate all the results that are presented in the paper.

Clearly, the increase in the number of observable buses increases the total annual cost because the total annual cost includes the operation cost, which is the cost of recharging the battery. Furthermore, increasing the number of observable buses increases the amount of consumed energy during flight between these buses and also increases the amount of

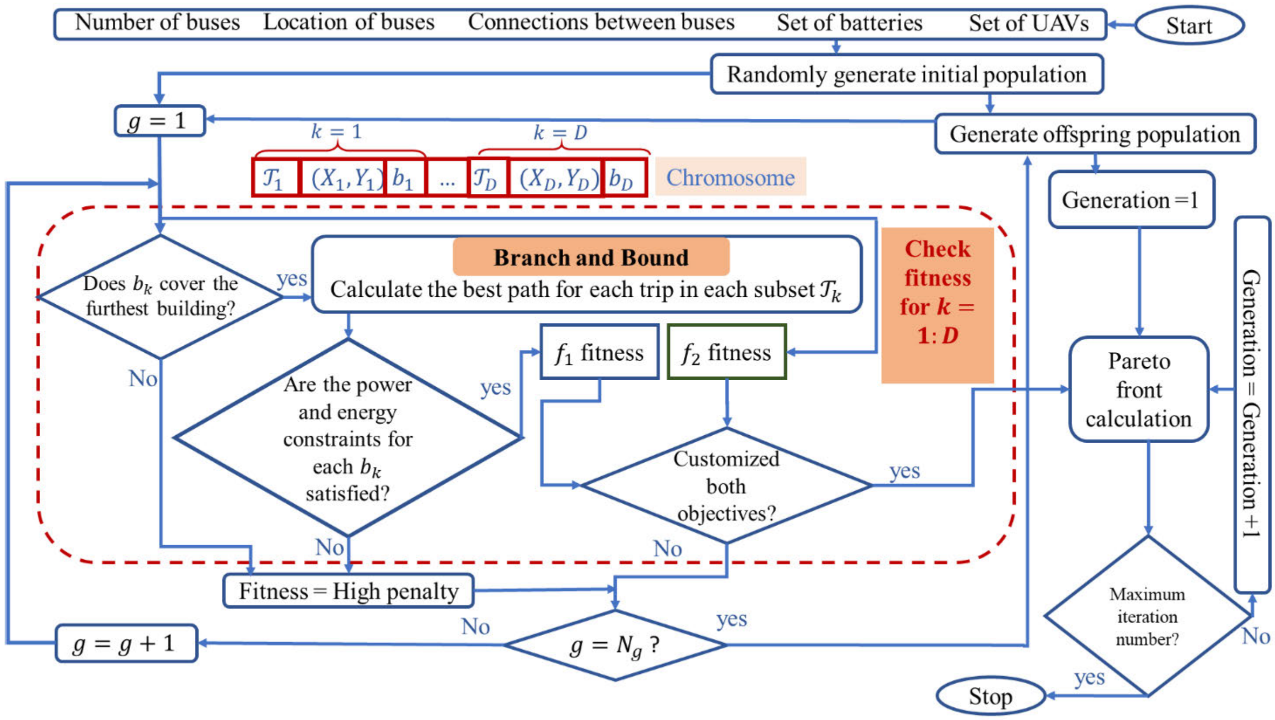

FIGURE 1. The proposed NDSGA-II algorithm flow chart.

TABLE 1. Simulation Parameters [34].

Parameters	Value	Parameters	Value
t_h	10 sec	A_d	0.045216 m^2
L_b^{cycle}	400	n_d	4 rotors
ϵ	80 %	φ	90 %
μ	\$10^{-4}	ω	12 monthly/52 weekly
L_{max}	5 years	$m_{0,d}$	0.94 kg
L_d^{year}	5 years		
τ	44 monthly/10 weekly (2 monitoring hours /day)	pr_d	\$526.7

consumed energy during hovering. For example, as shown in Fig. 3, which represents the Pareto frontier results for the EPRI-Ckt5 system in case of 2 hours monitoring per day every month, if the drone does not monitor any bus, the total annual cost is \$0 and the loss of observability is 100% as shown in point L. While at point A, the total annual cost is \$127.4 when a significant increase in the cost (from \$0 to \$127.4) despite a merely 0.3% increase in observability. This is because the cost of the drone and its battery exist even if only one bus is monitored. Also, the minimum total annual cost for monitoring all buses is \$226.5 as shown in point D as indicated in Fig. 3. In this particular scenario, the algorithm selects a drone with a small battery of 6,000 mAh @ 7.4 V to cover all buses and the charging point is found to be located at (395.85, 287.7). If the number of operating hours is reduced to one hour per day instead of two as shown in Fig. 4, the

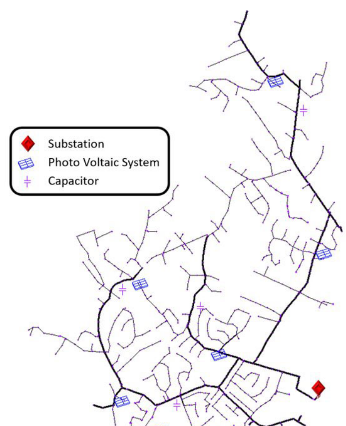

FIGURE 2. EPRI-Ckt5 system [30].

previously selected battery cannot provide adequate monitoring, so the 20,000 mAh @ 22.22 V bigger battery is selected, and the charging point is shifted towards the location (295.38, 208.17). Moreover, as shown in Figs. 3 and 4, increasing the number of observable buses increases the total annual cost. For example, the case of 33% loss of observability incurs a cost of \$176.7 annually in case of 2 working hours per day but this cost increases to \$239.3 per year in case of one working hour per day because of choosing a high-capacity battery.

In addition to the above, increasing the number of observable buses (decreasing the loss of observability) and the

TABLE 2. Candidate Batteries Specifications.

Battery	V	C	C^{rate}	m_b	Price ($)
1	11.1	350	70	0.11	8.12
2	11.1	450	70	0.12	12.18
3	11.1	1000	70	0.32	14.77
4	11.1	2200	25	0.18	15.12
5	11.1	1500	100	0.14	17.03
6	11.1	2200	25	0.41	18.62
7	11.1	2700	30	0.23	20.45
8	11.1	2200	25	0.29	20.82
9	7.4	6000	40	0.21	24.76
10	7.4	5000	50	0.2	36.50
11	11.1	7000	40	0.41	40.90
12	22.2	3200	60	0.51	48.6
13	11.1	3000	30	0.28	53.73
14	14.8	6000	50	0.59	56.7
15	22.2	5000	75	0.88	61.02
16	22.2	8000	60	1.24	85.59
17	22.2	10000	25	1.37	109.08
18	22.2	20000	25	1.5	148.64
19	22.2	22000	25	1.77	198.18

frequency of monitoring will inevitably lead to an increase in the number of drones. For example, Fig. 5 shows the Pareto frontier for the EPRI-Ckt5 system in case of weekly monitoring instead of monthly monitoring as previously studied. In this figure, Point A represents the results for 85.2% loss of observability with a total annual cost of $190.97 where one drone with battery 6,000 mAh @ 7.4 V is selected. On the other hand, point B represents the optimal solution for achieving 84.87% loss of observability with total annual cost $362.69 where two drones with batteries 22,000 mAh @ 22.2 V and 6,000 mAh @ 7.4 V are selected. Comparing the results with point C, we find that total annual cost greatly increases due to the need to use three drones while the observability only slightly increases. This is because the number of drones increases to two. Likewise, a similar observation holds at point D where four drones will be necessary.

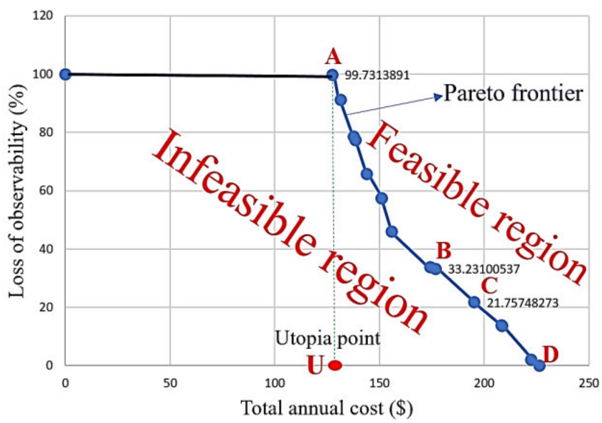

FIGURE 3. The Pareto frontier for the EPRI-Ckt5 system in case of 2-hours monitoring per day every month.

Finally, comparing Figs. 4 and 5, assuming only one working hour per day, if the monitoring frequency is monthly, one drone equipped with a 20,000 mAh @ 22.22 V is selected and the total annual cost is found to be $270.4 assuming 0% loss of observability. However, in case of weekly monitoring, for the case of 0% loss of observability, the cost increases to $1208.2 because four drones with batteries 22,000 mAh @ 22.2 V, two 20,000 mAh @ 22.2 V, and 6,000 mAh @ 7.4 V are selected to cover all buses. This means that for weekly monitoring, the number of drones and the total annual cost increases four times than in the case of monthly monitoring.

In order to find a suitable trade-off point of operation, we make use of the point U indicated in Figs. 3, 4 and 5. This point is referred to as the Utopia point defined as the point that simultaneously minimizes the observability and the total annual cost. Since this is an infeasible point, we find the nearest point from the Pareto frontier to point U.

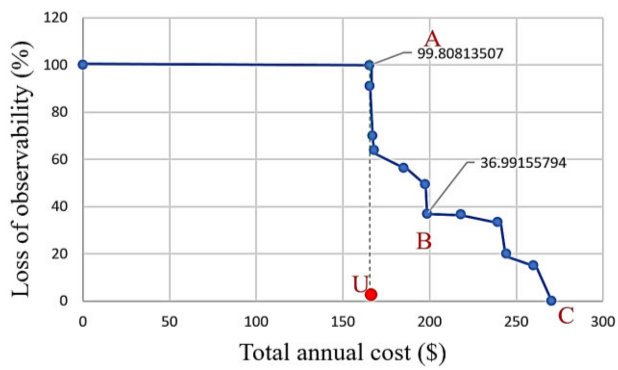

FIGURE 4. The Pareto frontier for the EPRI-Ckt5 system in case of 1-hours monitoring per day every month.

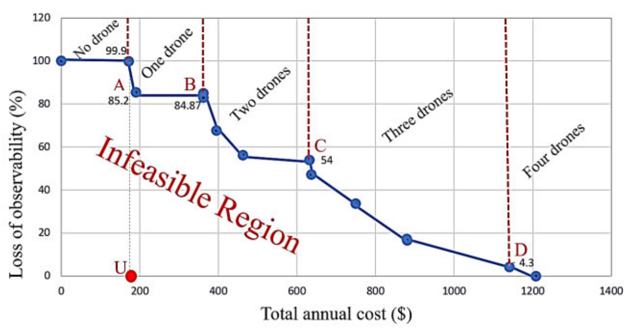

FIGURE 5. The Pareto frontier for the EPRI-Ckt5 system in case of 1-hour monitoring per day every week.

In order to check the sensitivity of the obtained optimal solution to the type of optimization algorithm used in the external sub problem as shown in Fig. 1, we performed a new simulation using a different optimization technique other than NDSGA-II, that is, simulated annealing (SA). Table 2 and Fig. 6 summarize the total annual cost and loss of observability obtained using both NDSGA-II and SA in case of 2-hours monitoring per day every month. It is clear that the new algorithm provides results that are very close to those obtained via NDSGA-II, emphasizing the stability of the optimization approach and showing that the optimal value was actually acquired. As shown in Table 2 and Fig. 6,

TABLE 3. **Comparison between NDSGA-II and SA Results.**

NDSGA-II		SA	
Cost ($)	Loss of observability	Cost ($)	Loss of observability
0	100	0	100
127.3827	99.73139	126	95.35
137.5358	78.66462	129.40	88.35
138.46	77.32157	138.46	77.32
150.8483	57.36761	145.99	65.69
155.8983	45.89409	153.50	59.00
176.6908	33.23101	186.94	45.09
195.2248	21.75748	214.4514	13.7375
208.4001	13.73753	235.65	9.998
226.5355	0	288.888	0

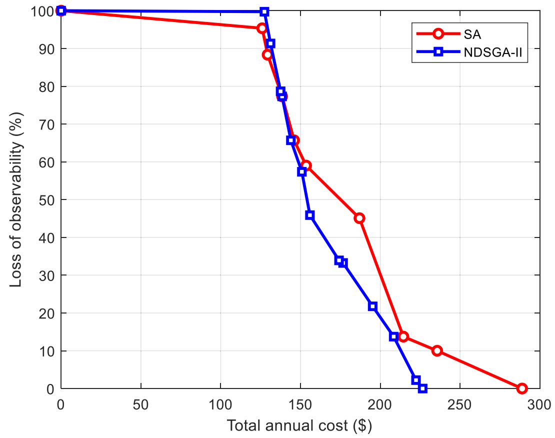

FIGURE 6. **Pareto fronts obtained using the NDSGA-II and SA algorithms.**

TABLE 4. **The maximum depth of discharching and total annual cost.**

The maximum depth of discharging (%)	Total Annual Cost ($)
80	226.5
70	260.5
60	299
50	15000

TABLE 5. **The maximum number of charging battery and total annual cost.**

The maximum number of charging battery	Total Annual Cost ($)
400	226.5
350	236
300	248
250	297.77
200	364.4

the results of using NDSGA-II are better than using SA, for example to achieve 0% loss in observability, the total annual cost equals $226.5355 when using NDSGA-II and equals $288.888 when using SA. Also, the total annual cost in the case of NDSGA-II is generally lower than in the case of using SA to achieve the same percentage of observation.

Finally, examination the effect of changing the percentage of the maximum depth of discharging in the total annual cost. In the case of 2 hours of monitoring per day every month and zero loss of observability, decreasing the percentage of the maximum depth of discharge increases the total annual cost as shown in Table 4. Also, decreasing the maximum depth of discharge increases the total annual cost as shown in Table 5.

VII. CONCLUSION

In this paper, we proposed a novel approach for distribution networks monitoring for situational awareness. The proposed approach relies on using drones equipped with contactless sensors to monitor overhead transmission lines. We formulated the problem as a multi-objective optimization problem to minimize the total annual cost and loss of observability. To solve the proposed problem, an outer sub problem is tackled using genetic algorithms and an inner sub problem is tackled using branch-and-bound. We used a non-dominated sorting genetic algorithm to create the set of Pareto optimal solutions.

The outcome of the proposed approach is the optimal number of drone(s) needed for system observability with their battery(ies) size, charging point location(s), the buses to be visited in each trip, and the optimal path for each trip. The proposed approach has been applied to the Epri-Ckt5 system assuming two different cases of frequency monitoring (monthly and weekly) and two different cases of number of working hours per day (1 hour/day and 2 hours/day). Simulation results proved the efficiency of the proposed approach.

It was found that, assuming monthly observation and 2 working hours/day, the algorithm selects a UAV with a small capacity battery 6,000 mAh @ 7.4 V to observe all buses. However, in case of a 1 working hour/day, a bigger capacity battery 20,000 mAh @ 22.22 V has been selected. It was also observed that if the observation is done weekly, more than one UAV will need to be chosen with their suitable batteries and charging locations.

As a possible extension to this work, methods for recharging the battery of the UAVs without the need to return to the charging location can be investigated and further incorporated into the studied problem. For example, this can be done by harvesting the energy from mobile base stations or by installing solar panels on the UAVs. Another possible direction that could be pursued is to use the same UAV for collecting data from smart meters and observing the distribution network at the same time.

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HAIAM SHAHIN received the B.Sc. degree in electronics and communication engineering from Mansoura University, Mansoura, Egypt, in 2008, and the M.Sc. degree in electronics and communications engineering from Cairo University, Cairo, Egypt, in 2021. She was a Teaching Assistant with Egyptian Russian University, Cairo, from 2011 to 2016. She is currently a Lecturer with the Arab Academy for Science, Technology and Marine Transportation, Khorfakkan Branch, Khorfakkan, United Arab Emirates. Her research interests include networks and wireless communications.

MOSTAFA F. SHAABAN (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees in electrical engineering from Ain Shams University, Cairo, Egypt, in 2004 and 2008, respectively, and the Ph.D. degree in electrical engineering from the University of Waterloo, Waterloo, ON, Canada, in 2014.

Currently, he is an Associate Professor with the Department of Electrical Engineering, American University of Sharjah, Sharjah, United Arab Emirates. He is also an Adjunct Associate Professor with the University of Waterloo. He was with Independent Electricity System Operator (IESO) of Ontario, Canada, where he was involved in developing generation and flow limits for the stable operation of the power systems. He was also with Opus One Solutions as a Clean Energy Consultant. He has several publications in international journals and conferences. His research interests include smart grids, renewable DG, distribution system planning, electric vehicles, storage systems, and bulk power system reliability. He serves as an Associate Editor for *IET Smart Grid* and IET *Energy Conversion and Economics*.

MAHMOUD H. ISMAIL (Senior Member, IEEE) received the B.Sc. degree (Hons.) in electronics and electrical communications engineering and the M.Sc. degree in communications engineering from Cairo University, Cairo, Egypt, in 2000 and 2002, respectively, and the Ph.D. degree in electrical engineering from the University of Mississippi, Oxford, USA, in 2006. From August 2000 to August 2002, he was a Research and Teaching Assistant with the Department of Electronics and Electrical Communications Engineering, Cairo University. From 2004 to 2006, he was a Research Assistant with the Center for Wireless Communications (CWC), University of Mississippi. He was a System Engineering Consultant with Newport Media Inc. (currently a part of Microchip), Cairo, from 2006 to 2014. He is currently a Full Professor with the American University of Sharjah, Sharjah, United Arab Emirates, and a Full Professor (on leave) with the Department of Electronics and Electrical Communications Engineering, Cairo University. His research interests include wireless communication, with an emphasis on performance evaluation of next-generation wireless systems, coexistence, vehicular networks, and communications over fading channel. He was a recipient of the University of Mississippi Summer Assistantship Award, in 2004 and 2005, the University of Mississippi Dissertation Fellowship Award, in 2006, the University of Mississippi Graduate Achievement Award in electrical engineering, in 2006, and the Best Paper Award at the tenth IEEE Symposium on Computers and Communications (ISCC 2005), La Manga del Mar Menor, Spain.

HEBAT-ALLAH M. MOURAD received the B.Sc., M.Sc., and Ph.D. degrees in electrical communication engineering from Cairo University, Cairo, Egypt, in 1983, 1987, and 1994, respectively. Since 1983, she has been with the Department of Electronics and Electrical Communications, Faculty of Engineering, Cairo University, where she is currently a Professor. She was the Director of the High Technology Center, Faculty of Engineering, Cairo University, from 2008 to 2012. She was a member of the Technical Office of the Post Graduate and Research Sector, Cairo University, from 2010 to 2012. She was named in Marquis Who's Who in Science and Engineering in 2004. Her research interest includes wireless and mobile communications.

AHMED KHATTAB (Senior Member, IEEE) was born in Cairo, Egypt, in 1980. He received the B.Sc. (Hons.) and M.Sc. degrees in electrical engineering from Cairo University, Cairo, Egypt, in 2002 and 2004, respectively, the master's degree in electrical engineering from Rice University, in 2009, and the Ph.D. degree in computer engineering from the Center for Advanced Computer Studies (CACS), University of Louisiana, Lafayette, in 2011. He is a Professor with the Electronics and Electrical Communications Engineering Department, Cairo University, where he joined in 2012, as an Assistant Professor. He has authored/coauthored three books, four book chapters, over 100 journals and conference publications, and U.S. patent. His current research interests include wireless networking, including the Internet of Things (IoT), wireless sensor networks, vehicular networks, cognitive radio networks, and security and machine learning. He was a recipient of the Egypt State First Class Medallion of Excellence, in 2019, the Egypt State Encouragement Award for Engineering Sciences, in 2017, and the Cairo University Excellence Award in Advanced Technology Sciences, in 2020. He has also won several awards from different IEEE conferences and societies.