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A Multi-Objective Hyper-Heuristic for Unmanned Aerial Vehicle Data Collection in Wireless Sensor Networks

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***Abstract*—Monitoring dangerous regions is one of the most important applications of wireless sensor networks. Limited by the danger of monitoring regions and the battery power of sensors, unmanned aerial vehicles (UAVs) are often used to collect data in such applications. How to properly schedule the movement of UAVs to efficiently collect data is still a challenging problem to be solved. In this paper, we formulate the UAV scheduling problem as a multi-objective optimization problem and design a genetic programming based hyper-heuristic framework to solve the problem. The simulation results show that our method can provide very promising performance in comparison with several state-of-the-art methods.**

***Keywords*—wireless sensor network; unmanned aerial vehicle; dangerous region; hyper-heuristics; multi-objective problem.**

I. Introduction

Wireless sensor network (WSN) has become an important technique for dangerous region monitoring, such as military detection [1]–[3], forest fire detection [4]–[6], and power line inspection [7], [8]. By deploying the WSN to monitor those dangerous regions, users successfully reduce human participation and improve efficiency. To collect the data from sensors, a data collector (i.e. the mobile sink in WSN) is designed to keep patrolling the monitoring region and buffering the data from sensors. By this means, the patrolling route of the mobile sink becomes one of the most important factors to maximize the network lifetime. There have been many algorithms for network lifetime maximization by mobile sink scheduling. For example, Luo et.al. [9] proposed a mixed integer linear programming method (MILP) to schedule the sink movement. Basagni et.al. [10] proposed a heuristic method (i.e. the greedy maximum residual energy (GMRE)) to solve the mobile sink scheduling problem by the greedy scheme. And Zhong et.al. [11] adopted the ant colony optimization algorithm (ACO), a stochastic search method, to search for the route of the mobile sink. However, existing methods mainly focus on maximizing the network lifetime, which is not sufficient enough in applications such as those involving unmanned aerial vehicles (UAVs) in dangerous regions.

Over the past decade, multi-objective techniques have been applied in WSN to improve the performance of different metrics [12], [13], varying from network latency [14], [15], network coverage and network lifetime [16], [17], to quality of service (QoS) and network security [18], [19]. And different strategies have also been proposed to solve these multi-objective problems in WSN, such as the sensor deployment scheduling [20]–[23] and the data routing design [24]–[26]. However, existing works are not effective enough for the applications of UAV in dangerous regions, since they do not fully consider the characteristics of UAVs and dangerous regions. For example, since UAVs are also battery-powered, energy conservation should be considered to extend the UAV working time. Besides, in dangerous regions (e.g. the hostile region and complex electromagnetic environment), the performance of UAVs is also affected. Bypassing these dangerous regions during scheduling the routes of UAVs is important.

To consider the above issues, in this paper, we design three metrics to measure the movement of the UAV: the network lifetime, the travel distance of UAVs, and the danger cost which measures the dangerous level of the sensing region. To schedule the UAV properly and optimize these metrics, we model the optimization problem as a multi-objective optimization problem and use a genetic programming based hyper-heuristic framework (GPHH) to solve the multi-objective problem. The multi-objective problem contains three objectives: maximizing the network lifetime, minimizing the travel distance of the UAV, and minimizing the danger cost. The GPHH is performed to automatically search for heuristics with different trade-offs among the three metrics. During the searching process of G-PHH, heuristics are generated using nature-inspired operators and then sorted by the non-dominated sorting strategy used in NSGA-II. Better heuristics are selected to form the new population for the next generation. In this way, better non-dominated heuristics can be generated by the proposed GPHH.

This paper makes the following contributions. Firstly, we formulate the UAV data collection problem in dangerous regions into a three-objective optimization problem and establish the corresponding mathematical model. Besides, we apply a hyper-heuristic framework combined with NSGA-II to design scheduling heuristics for UAV movement so that the performance of the UAV approximates the Pareto Front of the three-objective optimization problem.

The rest of the paper is organized as follows. The problem definition and its formulation are introduced in Section II. The hyper-heuristic framework solving the formulated multi-objective problem is introduced in Section III. Then, Section IV introduces the experiment settings, the experiment results, and their corresponding analyses. Finally, Section V concludes the paper based on the experiment results.

II. Problem Definition

In this section, we formulate the UAV data collection problem as a multi-objective mobile sink scheduling problem. Before the formulation, three main components (i.e. wireless sensor network, UAV data collection, and dangerous region) are introduced in detail to distinguish the UAV data collection problem in dangerous regions with other WSN applications.

A. Wireless Sensor Network

A typical WSN contains a set of sensors S whose size is the number of sensors n, and a set of candidate mobile sink sites C whose size is m, and one or more mobile sinks. The sensors are deployed in a physical environment to monitor the environment with a constant sensing rate r while the mobile sinks are moving around to collect the data from sensors. Usually, the sensors are battery-powered and can not be recharged when they run out of their power. Therefore, they all have a limited initial power $E_i(i \in S)$. In contrast, the mobile sinks are usually supposed to have enough energy during the network lifetime L. It should be noticed that, in this paper, the network lifetime L is defined based on the definition mentioned in [9] (i.e. The network is "dead" once at least one sensor runs out of its power $E_i \leq 0(\exists i \in S)$). The energy consumption of sensors is mainly caused by the wireless communication (i.e. data sending and data reception) when data aggregates to the mobile sink by multi-hop mechanism. We denote the consumption rate of data sending and data reception as $\mathbf{et}_i^l$ and $\mathbf{er}_i^l$ respectively, where i is the index of sensors and l is the index of different epochs. In this problem, $\mathbf{er}_i^l$ is a constant vector for all sensors while $\mathbf{et}_i^l$ is related to the distance between senders and receptors, as shown in (1). A and B are two constants predefined manually.

$$et_{i,j}^l = A \times {d_{i,j}^l}^2 + B \quad (1)$$

According to the consumption rate of data communication and the number of data packets, the energy consumption of data communication of each sensor is formulated as $\mathbf{et}_i^l \cdot \mathbf{p}_i^l + \mathbf{er}_i^l \cdot \mathbf{q}_i^l$, where $\mathbf{p}_i^l$ and $\mathbf{q}_i^l$ are the number of packets sent and received by sensor i in epoch l respectively. It is worth mentioning that, since both $\mathbf{p}_i^l$ and $\mathbf{q}_i^l$ are highly related to the energy consumption of sensors, the routing of data packets is also an important scheduling problem in WSN. But because the routing of data packets is not the focus of our paper, we adopt another well-known data routing method proposed in [27], named flow augmentation algorithm (FA), in our paper to schedule the data routing. The multi-hop mechanism is also built by the FA algorithm. Both sensors and sinks have a maximum communication range R. As a result, two sensors (or a sensor and a sink) i and j can transmit data packets in one hop only when the distance between them is less than or equal to R (i.e. $d_{i,j} \leq R$). When $d_{i,j} > R$, they can only transmit packets by the multi-hop mechanism. In this paper, all sensors are assumed to be reachable to the other sensors by the multi-hop mechanism.

As for the sink, it only sojourns at the candidate sink sites. Since the sink sites and the sojourn time at each sink site are different and continuous, we transform this continuous problem into a discrete one to simplify the model. On one hand, C should be a finite set. On the other hand, the mobile sink stays at a certain sink site for at least a minimum sojourn time Δt. It is defined as an epoch each time the sink stays for Δt and reselects the next sink site. In this way, the transformed problem and its routing algorithms become computable and feasible solutions can be found out, though the optimal solutions for the actual problem may not be included in the transformed problem [9]. Each time the sink moves to another sink site, the multi-hop tree connecting all sensors and the sink needs to be rebuilt based on the FA algorithm.

Based on the definition of Δt, the network lifetime L can also be further defined as (2), where t_c is the number of epochs that the sink stays at sink site c.

$$L = \sum_{c=1}^{m} t_c \quad (2)$$

Since different sink sites correspond to different multi-hop trees, which means different energy consumption of sensors, the route of sink movement is required to be scheduled properly so that the network lifetime can be maximized. It is worth mentioning that the travel time of the sink between two sink sites are not considered in L because the travel time is much smaller than Δt. During the running of the network, there are two conservation principles the sensors must obey (i.e. the energy conservation and the flow conservation) [9]. The energy conservation requires that the remaining energy of all sensors must be larger than or equal to 0 as shown in (3).

$$E_i - \sum_{l}(\mathbf{et}_i^l \cdot \mathbf{p}_i^l + \mathbf{er}_i^l \cdot \mathbf{q}_i^l) \geq 0, \forall i \in S \quad (3)$$

The flow conservation requires that total the number of data sent from sensor i must be equal to the sum of the sensing data of sensor i and the receiving data from other sensors (4), where r is the constant sensing data rate of all sensors.

$$\|\mathbf{p}_i^l\| - \|\mathbf{q}_i^l\| - r\Delta t = 0, \forall i \in S \quad (4)$$

B. UAV Data Collection

UAVs have been utilized as mobile sinks in many large-scale WSNs, such as disaster monitoring [28], [29] and structural health monitoring [30]. However, since UAVs are also battery-powered, the unlimited energy assumption on the mobile sink is impractical in UAV applications. Therefore, scheduling the UAV movement properly and reducing the UAV energy consumption is a critical issue for UAV applications in WSNs.

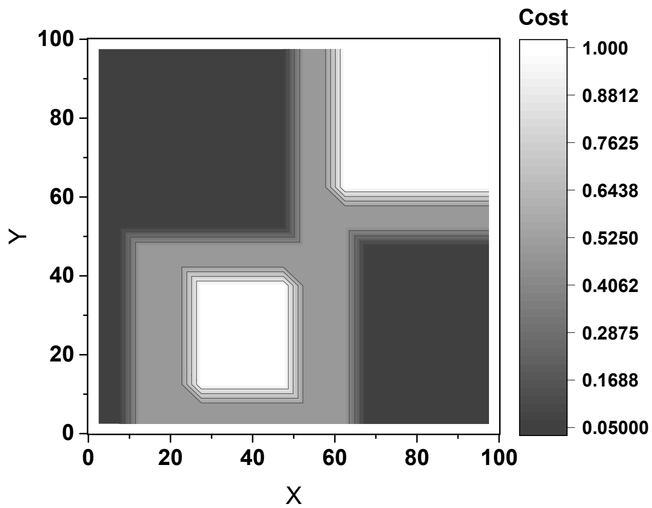

Fig. 1. The example danger cost map

In this paper, we use one UAV as the mobile sink of the WSN. To adopt the network lifetime defined in [9], there is no maximum energy limitation for UAVs, which means a UAV has enough power to keep working during the network lifetime. However, to make the obtained solutions practical, the UAV energy consumption is introduced as one of the quality metrics for solutions and solutions with lower energy consumption are considered as better. The energy consumption of the UAV mainly consists of two aspects: traveling and data communication. Since there is only one UAV, according to the flow conservation and the consumption rate of data reception (i.e. a constant), the energy consumption on data communication must be a constant value. Therefore, travel distance is the key issue to improve UAV energy efficiency. We use the UAV travel distance D to represent the energy consumption of UAV. D is formulated as the sum of the Euclidean distance of different sink sites in each epoch as shown in (5)

$$D = \sum_{l \geq 1} ||o^l - o^{l-1}||, o \in C \tag{5}$$

where o is the 2-D geographical coordinate of the UAV.

C. Dangerous Region

In many WSN applications, such as military detection, disaster monitoring, and power line inspection, dangerous regions are considered. For example, in military detection, the UAV has different being discovered probability in different regions. And in power line inspection, the UAV may be disturbed by the electromagnetic environment generated from the power line. To consider such kind of negative physical environment information in solutions, we build a danger cost map ϱ for each network. An example danger cost map in our paper is Fig.1. The dark region in the map means a safe region while the bright region means a dangerous region. The danger cost map describes the danger cost ρ the UAV has to pay when it enters different regions of the map. Since ϱ describes the danger such as being discovered probability and electromagnetic field, a solution with high final danger cost is regarded as uncompetitive and less beneficial. The ρ increases when the UAV stays at and travels across a certain region and it is calculated as shown in (6)

$$\rho = \varrho_{o^l} + \sum_i \varrho_{o_i}, o_i \in \textbf{segment } o^l o^{l+1} \tag{6}$$

where ϱ_{o^l} is the danger cost at coordinate o^l and o_i is the fix-step-length sample from segment $o^l o^{l+1}$. To reduce the ρ, the UAV needs to stay at the places with low ϱ and bypass regions with high ϱ.

D. Formulation

Based on the discussion above, we formulate the typical mobile sink scheduling problem in WSN into a new multi-objective problem. It contains three objectives: maximize the network lifetime L, minimize the UAV travel distance D, and minimize the danger cost of UAV ρ. They are shown as follows:

$$\begin{aligned} &\min F(\Gamma) = (f_1(\Gamma), f_2(\Gamma), f_3(\Gamma))^T \\ &\text{subject to} \\ &\qquad f_1(\Gamma) = \min -L(\Gamma) \\ &\qquad f_2(\Gamma) = \min D(\Gamma) \\ &\qquad f_3(\Gamma) = \min \rho(\Gamma) \\ &\qquad \Gamma \in \Omega \end{aligned} \tag{7}$$

where Ω is the decision space containing all feasible Γs and it is constrained by the energy conservation (3) and the flow conservation (4). Since L is a maximizing objective, we convert it as a minimizing objective by multiplying -1 to unify the formulation. In (7), f_1 usually contradicts the other two objectives, which means no Γ can minimize all these three objectives simultaneously. Therefore, the Γs with the best trade-off among these objectives form a Pareto Front theoretically. To solve F and obtain a set of Γs approximating the Pareto Front, the genetic programming based hyper-heuristic framework (GPHH) and NSGA-II are adopted.

III. Proposed Method

In this section, the genetic programming based hyper-heuristic framework (GPHH) is designed based on the previous work in [31] and the NSGA-II in [32]. First, the framework of our method to solve the multi-objective problem F is introduced. Then the components of our method such as the primitive design, hyper-heuristic discovery, and the selection strategy used in NSGA-II, are presented.

A. The Proposed Framework

In the heuristic-based UAV scheduling scheme, a UAV selects the next sink site every Δt according to a heuristic rule. This heuristic rule is specifically designed by human experts formerly such as the maximum residual energy heuristic (GMRE) proposed in [10]. To obtain a better heuristic rule so that the sink movement achieves better performance, we find a set of non-dominated Γ^*s by the hyper-heuristic framework, so that F can approximates the Pareto Front formed by f_1 to f_3.

Generally, in our method, a set of primitives is designed in advance based on domain knowledge. Then, in each generation of GPHH, different hyper-heuristics are constructed automatically based on these predesigned primitives. These constructed heuristics are then used to schedule the UAV movement on training networks to evaluate their fitness values. After that, the selection strategy based on non-dominated sorting and crowding distance used in NSGA-II [32] is performed to select a set of heuristics with better fitness values. After certain generations of evolution, the non-dominated heuristics in the population are outputted as the final results.

B. Implementation

The primitives are designed based on the ad-hoc knowledge. In this paper, we design six primitives for the genetic programming algorithm to design new heuristics. These six primitives are the minimum node's residual energy (λ), maximum node's residual energy (Λ), maximum local simulated network's lifetime (κ), maximum average node energy (μ), maximum average consumption rate of sensors (ν), and the danger cost of sink sites (ϱ_o). It is worth mentioning that, four of them have been introduced in our previous work [31]. Among them, Λ and ϱ_o are the newly designed primitives and ϱ has been introduced in II-C. In fact, Λ is the opposite with λ and it can be interpreted as the greedy maximum residual energy (GMRE), a popular heuristic rule proposed in [10]. And it can be calculated as follows,

$$\Lambda = \max g_i^l, \forall i \in S \text{ and } d(i,c) \leq R \tag{8}$$

where g_i^l is the residual energy of sensor i in epoch l and c is the site of the UAV.

Genetic programming (GP) is utilized to generate new heuristics. It is a special kind of genetic algorithm (GA) whose individuals can be decoded into mathematical formulas. By designing new heuristics and selecting the non-dominated heuristics by the selection strategy of NSGA-II, GP can design more suitable heuristics for different networks, which is a tedious work for a human. GP usually contains four main steps: initialization, reproduction, fitness evaluation, and selection. In this paper, we adopt a GP variant proposed in [33], named self-learning gene expression programming (SL-GEP). The primitives introduced above are used as the terminals for SL-GEP to construct heuristics (i.e. the individuals in SL-GEP). These initial heuristics are then repetitively modified by the genetic operations such as mutation and crossover, to generate new heuristics. Since the heuristics with better fitness survive in the population after selection, better heuristics in SL-GEP can be further improved after generations. The implementation details of SL-GEP (e.g. the chromosome representation) can be referred to [33]. In fact, other GP variants can also be applied here to discover new heuristics. In the simulation, the "sense-think-act" paradigm introduced in [31] is adopted as the heuristic-based scheduling scheme to schedule the UAV movement. The final UAV routing and its performance on three objectives can be obtained after the simulation. And based on the performance of three objectives, the selection strategy of NSGA-II is applied to select the non-dominated heuristics.

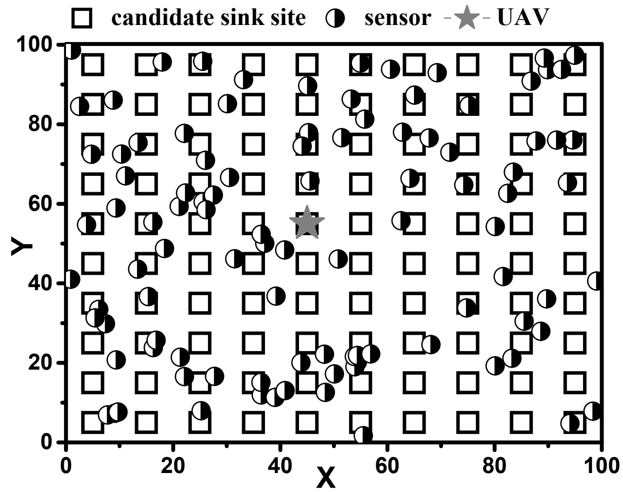

Fig. 2. The example network case

IV. EXPERIMENTS

To validate the performance of our method, we designed six kinds of networks which have twenty training network cases and ten testing network cases of each kind. And three other popular sink movement scheduling algorithms are also compared in our experiment. The experiment procedure consists of a training stage and a testing stage. In the training stage, our method is applied to each kind of training networks to design different heuristics. The outputted heuristics are then used to schedule the UAV movement in the testing networks in the testing stage to validate their performance.

A. Experiment Settings

We design six kinds of networks, indexed from "0" to "5". All these six kinds of networks have a uniform distribution of sensors and a same distribution of the candidate sink sites. Also, they have the same sensing region $(0, 100) \times (0, 100)$. The main difference among them lies on the problem scale (i.e. the number of sensors and sink sites). The number of sensors of these six network types ranges from 50 to 100. The example of network cases is shown as Fig.2. The other parameters of WSN are set the same as the existing work [9]. The sensing rate r, the least sojourn time Δt, and the coefficients A, B in (1) are set to be 1 bit/s, 3600 seconds, 50 nJ/bit, and 100pJ/bit/m2 respectively. The energy consumption for packet reception of every sensor and the initial energy of every sensor are 50 nJ/bit and 50 J respectively. The maximal communication range of sensors and the sink R is 30 meters. The multi-hop tree is constructed following the FA algorithm [27]. Table I lists all the detailed experiment settings.

TABLE I
THE PARAMETERS OF WIRELESS SENSOR NETWORKS

index	shared parameters	private parameters
0	$r_i = 1(bit/s)$ $\Delta t = 3600(sec)$ A=50(nJ/bit) B=100$(pJ/bit/m^2)$ $\mathbf{er}_i = 50(nJ/bit)$ $R = 30(m)$ $E_i = 50(J)$ sensing region $= (0, 100) \times (0, 100)$ Routing algorithm=FA [27]	$n = 50$, $m = 5 \times 5$
1		$n = 100$, $m = 5 \times 5$
2		$n = 50$, $m = 10 \times 10$
3		$n = 100$, $m = 10 \times 10$
4		$n = 50$, $m = 20 \times 20$
5		$n = 100$, $m = 20 \times 20$

TABLE II
THE HEURISTICS FOR DIFFERENT OBJECTIVES

index	objective	heuristics
0	L	$((((\lambda+(\mu-\kappa))/\Lambda)-((\kappa*((\lambda+\nu)*\mu))/(\kappa+((\lambda+\nu)*\mu))))-(((\lambda+(\mu-\kappa))/\Lambda)*((\lambda+(\mu-\kappa))/\Lambda)))$
	D	$((((\kappa-\nu)+(\varrho/\mu))*(((\varrho*\varrho)/\lambda)-((\kappa-\nu)+(\varrho/\mu))))*\Lambda)$
	ρ	$((((\kappa*\kappa)*(((\varrho/\mu)*\varrho)+(\varrho/\varrho)))+((((\varrho/\mu)*\varrho)+(\varrho/\varrho))/(((\varrho/\mu)*\varrho)+(\varrho/\varrho))))-((\kappa*((\lambda*\varrho)+(\varrho/\varrho)))+(((\lambda*\varrho)+(\varrho/\varrho))/((\lambda*\varrho)+(\varrho/\varrho)))))$
1	L	$(\lambda*((((\mu+\lambda)-\kappa)/(\nu-\kappa))-(\nu*(\varrho/\varrho))))$
	D	$(\mu*(((\nu-\lambda)+((\nu-\lambda)-((\varrho/\varrho)-\Lambda)))-((\varrho+\lambda)/(\varrho/\kappa))))$
	ρ	$((((\varrho+\varrho)*(\varrho/(\varrho/(\varrho*\varrho))))/(((\varrho+\varrho)*(\varrho/(\varrho/(\varrho*\varrho))))*((\varrho+\varrho)*(\varrho/(\varrho/(\varrho*\varrho))))))$
2	L	$((((\Lambda/(((\mu/\nu)/\nu)-(\nu/\nu)))-((((\mu/\nu)/\nu)-(\nu/\nu))/(((\mu/\nu)/\nu)-(\nu/\nu))))/\lambda)-(\lambda/\lambda))$
	D	$(\nu-((\Lambda+\Lambda)+((\varrho+\Lambda)/(\mu-\Lambda))))$
	ρ	$((\varrho/\varrho)-\varrho)$
3	L	$((((\kappa/\kappa)*\nu)/((\kappa/\kappa)*\nu))*((\lambda/\lambda)*((\lambda-\nu)-\kappa)))$
	D	$((\lambda-((\kappa/\Lambda)+\lambda))-(\lambda/((\Lambda/\lambda)/\kappa)))$
	ρ	$((\Lambda/((\lambda-\lambda)+(\lambda-\lambda)))/(\varrho+\varrho))$
4	L	$((((\kappa-\Lambda)+(\kappa-\Lambda))*(\Lambda/(\kappa-\Lambda)))/((\lambda*\mu)*(\nu*\kappa)))$
	D	$((\varrho-(((\mu-\lambda)*(\lambda/\mu))-\lambda))*((((\mu-\lambda)*(\lambda/\mu))-\lambda)/\varrho))$
	ρ	$((\mu*((\Lambda+(\varrho-\varrho))-(\Lambda+(\varrho-\varrho))))-(\varrho*\varrho))$
5	L	$((\Lambda/((\mu-\Lambda)-((\Lambda+\Lambda)*\Lambda)))*(((((\nu+\nu)*\nu)-\mu)+(((\nu+\nu)*\nu)-\mu))*(((\nu+\nu)*\nu)-\mu)))$
	D	$((\varrho/\nu)*((\varrho/\Lambda)+(\nu-(\lambda*\lambda))))$
	ρ	$(((\nu/(((\kappa*\mu)+\varrho)*\Lambda))-\varrho)*(\varrho-(\nu/(((\kappa*\mu)+\varrho)*\Lambda))))$

In our paper, three existing sink movement scheduling algorithms: linear programming method (LP(C-MB)) [34], ant colony optimization (ACO) [11], and greedy maximum residual energy (GMRE) [10] are adopted for comparisons. LP(C-MB) is a linear programming method which formulates the sink scheduling problem into a constrained linear programming problem. Since the number of dimensions of the solution is equal to the number of candidate sink sites, when the scale of networks increases, the computation time and the computation memory of LP(C-MB) become unbearable. ACO has been applied in many real-world applications and shown to be effective in WSN lifetime maximization [11]. Different from ACO, GMRE designs a heuristic to schedule the sink movement. Since there is no multi-objective method being applied to maximize the network lifetime by the sink movement scheduling, we use these three methods to validate the performance of our method in network lifetime maximization. All the parameters of the comparing methods are the same as their original papers. As for the SL-GEP used in the GPHH, the population size and the maximum generation are set to 100 and 500 respectively. The other parameters of SL-GEP are also set the same as its original paper [33].

B. Training Results

In the training stage, six network types are trained respectively. After training on each network type, we output the objective values of the final generation population. The distributions of the objective values on three objectives (i.e. L-versus-D projection, D-versus-ρ projection, and L-versus-ρ projection) are shown in Fig.3. Since the objectives conflict with each other, which means the increase of network lifetime L implies the increase of travel distance D and danger cost ρ (two minimum objectives), both L-versus-D projection and L-versus-ρ projection present arc shapes close to the Pareto front on six training network types. In contrast, the D-versus-ρ projection does not present an approximated Pareto front toward the D and ρ minimum on six training network types. This is because ρ and D are not trade-off objectives. A solution with large D can have either large ρ (i.e. the sink moves a long distance in high-cost regions) or small ρ (i.e. the sink moves in low-cost regions), and vice versa. Fig.3 suggests that a series of non-dominated solutions on these objectives can be found by our method.

Besides pursing the non-dominated solutions, these heuristics are applied to the testing networks to validate the quality of these computer-designed heuristics. Since different non-dominated solutions have different performance in UAV scheduling, the heuristic rules with the longest network lifetime, smallest D, and smallest ρ on different training network types are selected separately for the UAV scheduling on testing networks. All these selected heuristics on each network type are listed in Table II. These heuristics found by GP are too complex to be understood by humans. But based on them, some features can still be highlighted. For example, the maximum average consumption rate of sensors ν, the minimum node's residual energy λ, and the maximum node's residual energy Λ are concerned by most heuristics, which means these three kinds of information may be important for this multi-objective problem. And it is worth mentioning that the danger cost of different regions ϱ plays an important role in the heuristics for objective ρ. ϱ is not only considered by all heuristics for ρ, but also has a high frequency in those heuristics. On the contrary, ρ are not considered in most heuristics for network lifetime maximization (e.g. the heuristics for L objective on "0", "2", "3", "4", and "5" network types). It implies that it might be not suitable to take ρ into consideration in the network lifetime maximization.

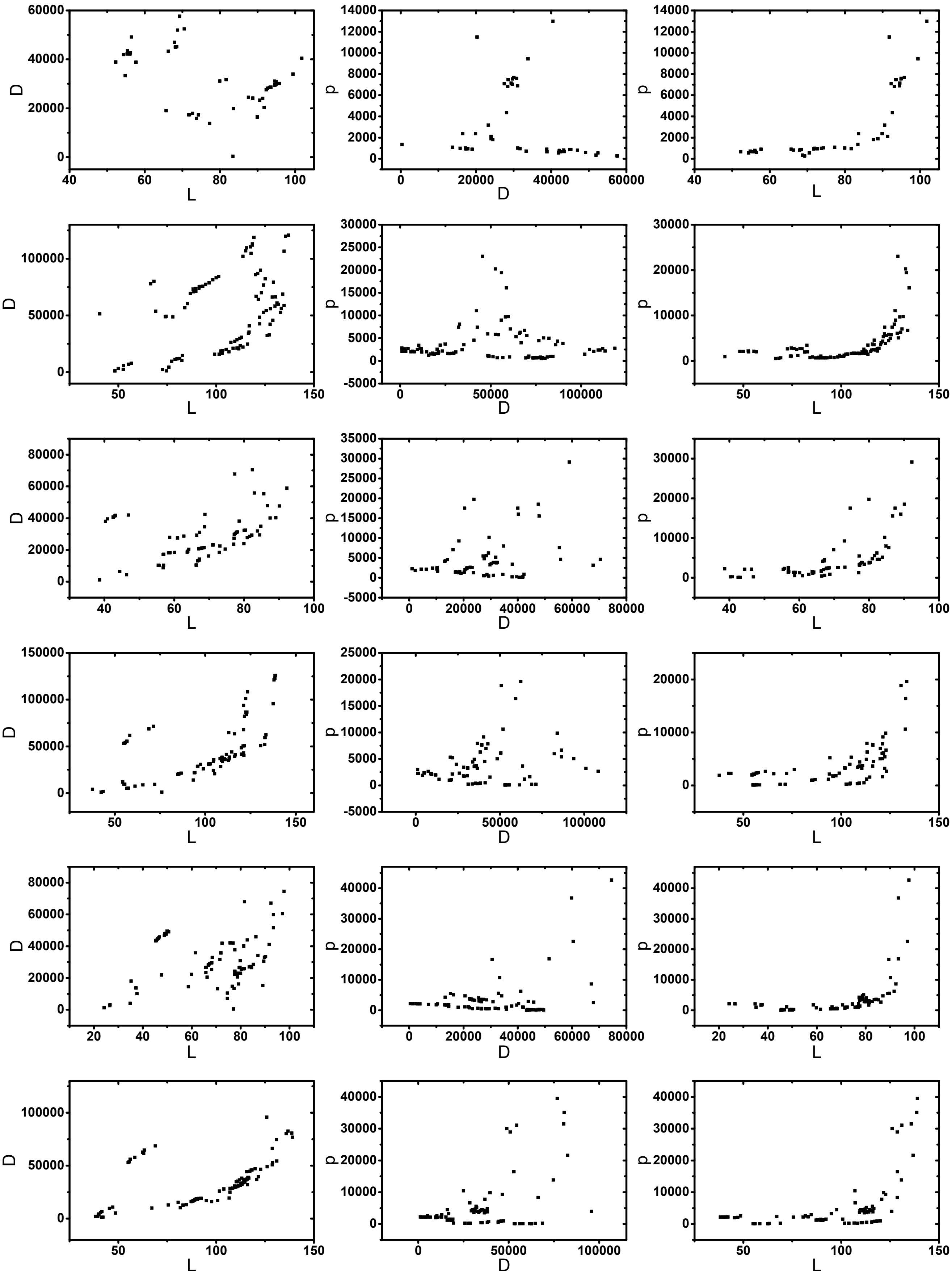

Fig. 3. The objective values of training

TABLE III
THE NETWORK LIFETIME OF TESTING WIRELESS SENSOR NETWORKS

index		LP(C-MB)	ACO	GMRE	Our method
0	AL	130.33	94.20	64.1	84.1
1	AL	N/A	139.9	87	107.9
2	AL	N/A	110.0	64.9	94.4
3	AL	N/A	144.5	99.0	122.1
4	AL	N/A	107.4	65.0	88.7
5	AL	N/A	152.6	111.7	88.4

TABLE IV
THE UAV TRAVEL DISTANCE OF TESTING WIRELESS SENSOR NETWORKS

index		LP(C-MB)	ACO	GMRE	Our method
0	AD	N/A	1058.4	4897.5	70.71
1	AD	N/A	1201.5	4877.7	74.95
2	AD	N/A	1972.9	3828.5	63.64
3	AD	N/A	2097.4	7404.6	84.45
4	AD	N/A	1933.1	4522.3	67.18
5	AD	N/A	2845.4	7594.0	67.18

C. Testing Results

The testing results are listed in Table III to Table V. On the testing networks, the average values of all the testing networks in the same network type are used as the metrics of different methods (i.e. the average lifetime AL, the average UAV travel distance AD, and the average danger cost $A\rho$). The heuristics listed in Table II and the three comparing algorithms are used to schedule the UAV movement on testing networks for corresponding objectives.

For the results of network lifetime shown in Table III, LP(C-MB) reaches the maximum AL on the first network type benefited from the constrained linear programming model. But it cannot solve the network types with larger scales (i.e. network "1" to "5") since its computing complexity is too high. ACO, a stochastic search method which searches solutions and evolves them in the whole solution space of the network, has the performance following LP(C-MB) on network "0" and has the best network lifetime maximization performance on network "1" to "5". GMRE, a mobile sink routing heuristic designed by human experts, performs worse than ACO on all six network types, since it does not utilize the prior knowledge of different networks and cannot adaptively update its solutions. As for our method, we use the heuristics with largest L to schedule the UAV movement on the testing networks. The heuristics designed by our method have better performance than GMRE in most network types (i.e. network "0", "1", "2", "3", and "4") and have competitive performance with ACO in some network types (i.e. network "0", "2", and "3").

As for the UAV travel distance and the danger cost shown in Table IV and Table V, the heuristics with the minimum travel distance D or minimum danger cost ρ from our method have satisfactory performance on the testing networks. They have much smaller values than others on both these two objectives. For LP(C-MB), since the solutions of LP(C-MB) are sets of sojourn time of different candidate sink sites, instead of sequences of UAV visiting sink sites, both the travel distance and the danger cost of LP(C-MB) solutions cannot be calculated. For the other two comparing methods, since they do not consider the travel distance and the danger cost, both AD and $A\rho$ are much larger than those of our method.

To summarise, the heuristics designed by our method have competitive performance compared with other network lifetime maximization methods on L. Besides, our method considers different objectives such as the minimization of travel distance D and the danger cost ρ, and has much better overall performance. It can be concluded that our method can flexibly satisfy different requirements from users by selecting different solutions on Pareto fronts and the performance of heuristics provided by our method is promising.

11.5
TABLE V
THE DANGER COST OF TESTING WIRELESS SENSOR NETWORKS

index		LP(C-MB)	ACO	GMRE	Our method
0	$A\rho$	N/A	715.2	63.1	28.6
1	$A\rho$	N/A	844.2	86.0	48.3
2	$A\rho$	N/A	1390.2	63.9	31.9
3	$A\rho$	N/A	1260.2	98.5	39.5
4	$A\rho$	N/A	1185.0	66.4	23.2
5	$A\rho$	N/A	1869.2	110.3	29.0

V. CONCLUSION

In this paper, we proposed a genetic programming based hyper-heuristic framework to schedule the movement of UAV to collect data in dangerous regions. We first model the problem into a three-objective optimization problem. Then, various primitives are designed for the hyper-heuristic framework to construct solution. After training based on networks with different features, the proposed method can output a set of non-dominated heuristics with different trade-offs among the three objectives. And the decision makers can flexibly select solutions from the final solution set based on their preferences. The empirical simulation results have demonstrated that the proposed method can provide very promising performance.

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