Hierarchical Multiobjective RFID Network Planning Using Firefly Algorithm

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***Abstract*—This paper presents implementation of the firefly algorithm adapted for solving hierarchical multi-objective radio frequency identification (RFID) network planning problem. This problem belongs to the group of hard optimization problems since it employs many objectives and constraints. Firefly algorithm has been proven as a robust algorithm for solving such tasks. We used hierarchical approach where total coverage was required, along with minimization of the number of used readers, interference and transmitted power. Empirical tests were conducted on six standard RFID benchmark sets with clustered and random topologies. In comparative analysis with other state-of-the-art metaheuristics which were tested using the same benchmark sets, our proposed approach exhibited uniformly better performance.**

Keywords–RFID network planning; firefly algorithm; swarm intelligence; nature inspired algorithms; constrained optimization

I. Introduction

In the recent years, radio frequency identification (RFID) technology has been widely adopted in many industries due to its great potential [1]. In the RFID applications in various fields such as logistics, production, supply chain management and asset tracking, a sufficient number of readers should be deployed with the goal of establishing a complete coverage of all tags in the respective domain [2]. RFID technology is also a cornerstone for the new concept of the Internet of things (IoT), which is a network that connects physical things to the Internet that makes it possible to access remote sensor data and to control the physical world form distance [3]. As a large-scale environment, IoT rises some important challenges that refer to the deployment of a RFID, such as optimal tag coverage, cost efficiency and the quality of service [1]. These challenges are known in the literature as multiobjective RFID network planning problem (MORNP) [4].

The goal of solving MORNP is optimization of a set of objectives (tag coverage, load balance, economic efficiency, readers' interferences, etc.) by adjusting the control variables (readers' coordinates, the number of readers, antenna parameters, etc.) of the system [3]. MORNP is high-dimensional, nonlinear problem, with conflicting objectives, and as such is hard for optimization by traditional techniques [5]. Thus, for the MORNP optimization, a usage of population-based stochastic metaheuristics could obtain better performance.

This research is supported by Ministry of Education, Science and Technological Development of Republic of Srbia, Grant No. III-44006

Metaheuristics are approximate and non-deterministic methods widely recognized as an efficient approach for many hard optimization problems. This paper deals with the firefly algorithm that belongs to the swarm intelligence metaheuristics. Swarms consist of relatively simple individuals (ants, bees, fish, worms, etc.) that exhibit intelligent collective behavior.

Swarm intelligence has been applied to the MORNP optimization. In majority of implementations, a weighted sum approach was used to transform MORNP optimization into a single-objective [6]. Some of swarm intelligence applications to RNP problem include multi-colony bacterial foraging optimization [7], plant growth simulation algorithm [2], cooperative multi-objective artificial bee colony and hierarchical artificial bee colony algorithm [1]. It is also possible to calculate Pareto front [8], [3].

In this paper, we show implementation of the firefly algorithm (FA) adapted for the MORNP optimization. Principles of the FA are based on the flashing behavior of fireflies in nature. FA was first proposed in 2008 by Yang for unconstrained optimization [9], [10], [11]. Later, it was widely adopted and applied to various problems [12], [13], [14], [15]. We used hierarchical approach since objectives are easy to order.

The approach was tested on six standard MORNP benchmark sets as proposed in [6]. To test the effectiveness of our implementation, we performed comparative analysis with other state-of-the-art algorithms.

II. Multiobjective Radio Frequency Identification Network Planning Formulation

RFID systems consist of tags and readers which communicate with each other by radio waves through antennas. Tags are attached to the items that are subject of tracking and they store unique identification number using a small integrated circuit [5]. Readers read from and write information to the tags.

Many MORNP models exist in the literature. In this section, we emphasize model, which we used in our experiments, and which was also employed in [6].

The assignment of the RNP problem is to deploy RFID readers in the working domain while reaching the following goals: maximum tag coverage, minimum number of readers, minimal interference and the minimal sum of transmitted power [6].

Achieving maximum level of *tag coverage* is the primary goal of the MORNP. To define this objective, bi-directional communication (reader to tag and tag to reader) should be taken into account. Any tag $t \in TS$ is covered by the reader, if and only if there is a reader $r_1 \in RS$ that satisfies $PT_{r_1,t} \geq T_t$ and a reader $r_2 \in RS$ satisfying $PR_{t,r_2} \geq T_r$. Here, $PT_{r_1,t}$ is the power received by the tag t from the reader r_1, and PR_{t,r_2} is the backscatter signal received by the reader r_2 from the tag t, and T_t and T_r are tag and reader sensitivity thresholds, respectively. $PT_{r_1,t}$ and PR_{t,r_2} are calculated according to Eq. (1) and Eq. (3) respectively [6]:

$$P_t[dBm] = P_1[dBm] + G_r[dBi] + G_t[dBi] - L[dB], \quad (1)$$

where P_1 is reader's transmitted power, G_r and G_t are reader's and tag's antenna gains respectively, and L denotes attenuation factor calculated by Friis transformation [16]:

$$L[dB] = 10log[(4\pi/\lambda)^2 d^n] + \delta[dB], \quad (2)$$

where d is a physical distance between the reader and the tag, n is environmental factor that varies from 1.5 to 4 due to changes in physical conditions, while δ represents losses in wireless communication.

The power received by the reader can be calculated as:

$$P_r[dBm] = P_b[dBm] + G_r[dBi] + G_t[dBi] - 20log(4\pi d/\lambda), \quad (3)$$

where P_b represents backscatter power sent by the tag. P_b depends on the tag reflection coefficient Γ and on the tag received power P_t (in watts):

$$P_b = (\Gamma_{tag})^2 P_t \quad (4)$$

Finally, the coverage rate of a network is defined as:

$$COV = \sum_{t \in TS}^{max} Cv(t)/N_t \cdot 100\%, \quad (5)$$

where

$$CV_t = \begin{cases} 1 & if \ \ni r_1, r_2 \in RS, \ PT_{r_1,t} \geq T_t \wedge PR_{t,r_2} \geq T_r \\ 0 & otherwise, \end{cases} \quad (6)$$

where $N_t = |TS|$ represents the number of tags distributed in the working domain.

In the literature, there can also be found formulations of this objective which consider only the power received by the tag. The optimal level of coverage is formulated as the sum of the difference between the desired power level P_d and the power that is received P_i^r of each tag i [5].

The second most important goal is to minimize the *number of readers*, because the network cost strongly depends on this factor.

When multiple readers interrogate the tag simultaneously, *interference* could happen. Important goal of RFD deployment is to decrease this interference which is calculated as the sum of interference levels at all deployed tags [6]:

$$INT = \sum_{t \in TS} \gamma(t), \quad (7)$$

where

$$\gamma(t) = \sum PT_{r,t} - max\{PT_{r,t}\}, \ r \in RS \wedge PT_{r,t} \geq T_t \quad (8)$$

The objective of *transmitted power* minimization is the least important, due to the fact that by reducing power, the most important objective of tag coverage could be jeopardized (refer to Eq. (3) and Eq. (1)). This objective can be modeled as [6]:

$$SPOW = \sum_{r \in RS} PS_r, \quad (9)$$

where PS_r denotes the transmitted power of the reader r.

III. Firefly Algorithm for MORNP

Firefly algorithm (FA) mimics flashing behavior of fireflies. Basic principle of this approach is that each firefly moves towards the brighter one.

The light intensity of fireflies in the population follows the inverse square law by

$$I(r) = \frac{I_0}{1 + \gamma r^2} \quad (10)$$

where $I(r)$ is the light intensity, r is distance, I_0 is the light intensity at the source and γ is the light absorption coefficient.

The attractiveness β of a firefly is proportional to its brightness [10]:

$$\beta(r) = \frac{\beta_0}{1 + \gamma r^2}, \quad (11)$$

where β_0 is the attractiveness at $r = 0$.

The process of search space intensification depends on attractiveness, and when firefly j is more attractive (brighter) than firefly i, firefly i is moving towards j:

$$x_i(t) = x_i(t) + \beta_0 r^{-\gamma r_{i,j}^2}(x_j - x_i) + \alpha(rand - 0.5), \quad (12)$$

where β_0 is attractiveness at $r = 0$, α is randomization parameter, $rand$ is random number uniformly distributed between 0 and 1, and $r_{i,j}$ is distance between fireflies i and j. This distance is calculated using Cartesian distance form:

$$r_{i,j} = ||x_i - x_j|| = \sqrt{\sum_{k=1}^{D}(x_{i,k} - x_{j,k})}, \quad (13)$$

where D is the number of problem parameters.

FA pseudo-code is available in [10]. Our implementation is this pure version of the FA, modified for particular objective function. Each firefly was represented as a real vector with

TABLE I
EXPERIMENTAL RESULTS

Algorithm	**Mean**				**Best**			
	Coverage	ReaderN	Interfer.	Power	Coverage	ReaderN	Interfer.	Power
Results for benchmark C30								
FA	100.00 %	**2**	0.000	**16.460**	100.00 %	**2**	0.000	**15.600**
GPSO	100.00 %	6	0.000	35.074	100.00 %	6	0.000	31.865
VNPSO	100.00 %	6	0.000	34.762	100.00 %	6	0.000	31.951
GPSO-RNP	100.00 %	3.18	0.000	35.511	100.00 %	3	0.000	33.948
VNPSO-RNP	100.00 %	3.04	0.000	35.034	100.00 %	3	0.000	33.535
Results for benchmark C50								
FA	100.00 %	**4**	0.000	**27.191**	100.00 %	**4**	0.000	**20.871**
GPSO	95.60 %	6	0.000	35.170	100.00 %	6	0.000	31.852
VNPSO	99.20 %	6	0.000	35.023	100.00 %	6	0.000	31.742
GPSO-RNP	100.00 %	5.04	0.000	36.244	100.00 %	5	0.000	33.418
VNPSO-RNP	100.00 %	5.06	0.000	36.565	100.00 %	5	0.000	34.522
Results for benchmark C100								
FA	100.00 %	**4**	0.000	**33.129**	100.00 %	**4**	0.000	**28.685**
GPSO	98.34 %	6	0.002	38.652	100.00 %	6	0.000	37.374
VNPSO	99.72 %	6	0.000	38.167	100.00 %	6	0.000	36.803
GPSO-RNP	100.00 %	5.16	0.000	38.800	100.00 %	5	0.000	37.513
VNPSO-RNP	100.00 %	5.04	0.000	38.513	100.00 %	5	0.000	37.449
Results for benchmark R30								
FA	100.00 %	**5**	0.000	39.841	100.00 %	**5**	0.000	**33.894**
GPSO	92.13 %	6	0.000	38.849	100.00 %	6	0.000	38.842
VNPSO	94.53 %	6	0.000	38.849	100.00 %	6	0.000	38.655
GPSO-RNP	99.87 %	7.46	0.002	39.821	100.00 %	6	0.000	39.265
VNPSO-RNP	100.00 %	6.86	0.003	40.143	100.00 %	6	0.000	39.574
Results for benchmark R50								
FA	100.00 %	**5**	0.004	43.285	100.00 %	**5**	0.000	**37.097**
GPSO	92.52 %	6	0.000	39.692	98.00 %	6	0.000	40.520
VNPSO	93.96 %	6	0.000	**39.690**	98.00 %	6	0.000	39.595
GPSO-RNP	99.84 %	8.26	0.012	40.652	100.00 %	7	0.000	40.315
VNPSO-RNP	100.00 %	7.66	0.030	40.667	100.00 %	7	0.000	40.080
Results for benchmark R100								
FA	100%	**5**	0.016	44.987	100.00 %	**5**	0.006	42.249
GPSO	91.18 %	6	0.014	**40.074**	95.00 %	6	0.000	**40.098**
VNPSO	94.14 %	6	**0.012**	40.333	97.00 %	6	0.043	40.657
GPSO-RNP	99.74 %	9.24	0.118	41.505	100.00 %	8	0.000	40.925
VNPSO-RNP	100.00 %	8.44	0.242	41.462	100.00 %	8	0.000	41.031

the dimension of $3M$, where M is the number of used RFID readers. First two dimensions are used for the representation of coordinates of the readers' positions, and the third dimension encodes radiated power of each reader. These parameters are used to optimize tag coverage, interference and transmitted power. The objective function is not the weighted sum and does not include penalty. Hierarchical approach is used, where tag coverage is the dominant factor that has to be improved by changing positions of readers. Only when the tag coverage reaches 100%, the second factor i.e. power minimization is activated with significant reduction in the position of the reader movement. Power control then minimizes both, interference and transmitted power.

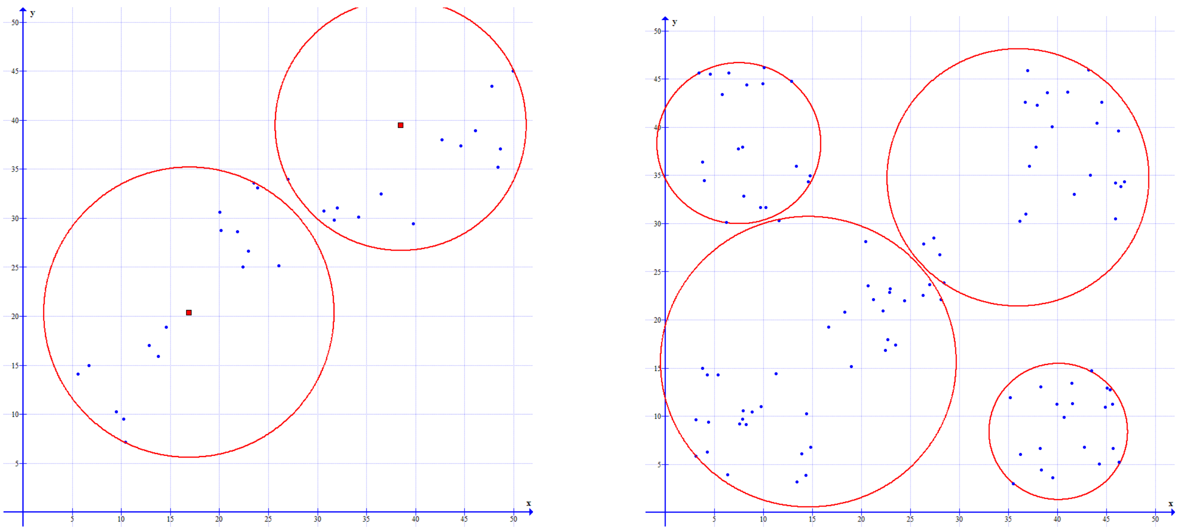
The number of readers could be the fourth optimization variable, however changing the number of readers completely disrupts the current state, effectively destroying exploitation which makes algorithm wildly oscillate. Since the number of possible readers is rather small, considering the size of the working area and the range of the readers, we introduced control in the algorithm for the change of the number of readers, giving the algorithm necessary time to converge before starting essentially new search with new number of readers.

IV. Experimental Results

When conducting empirical tests, we used six RNP instances: $C30$, $C50$, $C100$, $R30$, $R50$ and $R100$ with clustered and random topologies and 30, 50 and 100 tags, respectively. All benchmark instances were taken from the public URL: http://www.ai.sysu.edu.cn/GYJ/RFID/TII/. The same tests were performed in [6].

We considered readers with adjustable power in the range $[20, 33] dBm$ (0.1 to 2 watts). Wave length λ was set to 0.328m (915 MHz), sensitivity thresholds of tags and readers were $T_t = -14\ dBm$ and $T_r = -80\ dBm$, with corresponding antenna gains of $G_t = 3.7\ dBi$ and $G_r = 6.7\ dBi$. We set in Eqs. (1–4) δ to 2, n to 2, and Γ_{tag} to 0.3. Again, for comparison purposes, these values are the same as in [6]. All readers used in the benchmarks are mobile, and tags are static.

For FA settings, we set the population size N to 20, with 20,000 iterations. The same number of objective function evaluations was used in [6]. Parameters α, β_0 and γ were set to 0.5, 1.0 and 0.2, respectively.



(a) C30 (b) C100

Fig. 1. Optimal solutions examples

A comparative analysis was performed with GPSO (traditional PSO with the global topology), VNPSO (traditional PSO with the von Neumann topology), and GPSO-RNP and VNPSO-RNP as corresponding algorithms with incorporated tentative reader elimination (TRE) and mutation [6].

All experiments were conducted with 50 independent runs with different random number seeds. We show the best and mean values for all objectives.

Table I shows experimental results. For better comparison, best results from each category are marked bold. It can be seen that our proposed FA approach uniformly outperforms other compared algorithms. It achieves 100% coverage in all cases, so the most important objective is perfectly satisfied. Our approach also deploys significantly fewer readers, which is the second most important criterion. The interference is minimal with significant reduction in transmitted power (radiated power is shown in the Table). Fig. III illustrates the quality of results by two examples, $C30$ and $C100$ clustered benchmarks, where it is obvious that the proposed algorithm finds good solution with appropriately determined clusters and minimal power (some tags are on the edge of the covered area).

V. Conclusion

In this paper, we presented firefly algorithm (FA) for multi-objective RFID network planning problem. We tested our approach on six standard benchmark sets. A comparative analysis with other state-of-the-art shows that FA is very effective as RFID network optimizer.

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