Introduction of Dynamic Virtual Force Vector in Particle Swarm Optimization for Automated Deployment of RFID Networks

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***Abstract*—A scheme for automated planning of passive RFID network is proposed. The scheme comprises two parts. The first part creates a fast site-specific probabilistic propagation model for successful identification from the reader of any possible tag antenna. The materials of surrounding walls as well the tag antenna's radiation pattern, the geometry and the polarization of both reader and tag are taken into account. In the second part, a hybrid form of particle swarm optimization (PSO) algorithm is applied. The proposed approach selects a subset of tag antenna configurations to be installed so that a given cost function is satisfied. By clustering problematic areas during each iteration and moving the swarms towards them, we imitate the acts of a human-planner. The combinatorial performance of all active readers is evaluated at each tag location; this reveals that good identification performance is recorded at overlapping regions, where no single reader- tag antenna operates adequately. The proposed clustering approach greatly improves the convergence-time of the standard PSO and greatly reduces equipment, cutting down the cost of the network accordingly. Comparison with standard PSO reveals that the overall equipment can be reduced by a factor of two, satisfying the same quality constraints.**

***Index Terms*—RFID, Network-planning, Optimization.**

I. Introduction

Complex RFID networks are expected to control large facilities, e.g. warehouse or an airport. Due to the small range of RFID systems involving passive tags, such networks are expected to include hundreds of RFID antennas. The problem of planning an RFID network (deployment problem) involves the selection of appropriate antenna locations so that a given cost function, e.g. number of antennas, is minimized under specific quality constraints, e.g. identification percentage in the target volume, [1]-[11]. It has been shown in [10] that this problem is NP-complete. As a consequence, solutions are sought by employing evolutionary algorithms.

Prior art in the field was focused on deploying Wireless Sensor Networks (WSNs). The particularity of the RFID-deployment problem, with respect to WSNs, results from the fact that typically RFID tags are battery-less. In [12], we proposed a site-specific probabilistic model, where the probability of successful identification of a passive RFID tag is estimated by the appropriate Rician cumulative distribution function (cdf) in *small running time*, considering:

- the reader-antennas' radiation pattern,
- the polarization of the field,
- the polarization of the tag's antenna.

The accuracy of the model was verified against theoretical estimations from ray-tracing models [12], computational-electromagnetics models [14] and measurements [12]-[14]. The probabilistic propagation model has been successfully deployed in the standard Particle Swarm Optimization (PSO) method, presented in [3], demonstrating a two-times reduction of the necessary RFID readers to be installed, with respect to binary propagation models; i.e. such models define a closed area/volume around the reader antenna, where successful identification is guaranteed by the corresponding antenna, but cannot handle overlapping coverage zones between adjacent antennas.

However, the solution of the standard PSO in [3] is far from being optimal; i.e. the solution that minimizes equipment (cost), while satisfying given coverage constraints. Furthermore, convergence of the PSO (even to a non-optimal solution) is very slow; the random nature of PSO demands many iterations for modest improvements.

In this paper, we propose a hybrid PSO algorithm. The proposed method borrows properties from "Artificial Potential Field" (APF) algorithms, [7]-[8]. In APF, areas of preferential coverage will exert a "virtual attractive force" while obstacles and areas of non-preferential coverage will exert a repulsive force on the nodes. Additional forces may be considered, e.g. repulsive force between nodes. The total force on each node is the vector-sum of the above, eventually (after iterations) moving each node towards its final position. In the proposed method, an additional velocity vector is added to the standard PSO. After each iteration, the vector drags (similarly to the "virtual attractive force" of "APF") the swarm towards locations with identification-probability below the desired threshold, imitating the actions that would have been taken by a human planner. To accomplish that, *clustering* of problematic locations is carried out and the appropriate velocity vector is calculated for each antenna, based on its distance from the nearest cluster.

Results demonstrate *i)* a **two-times improvement** vs. standard PSO with respect to the number of antennas of the final solution that are needed, so as to meet the quality constraints and *ii)* significant **acceleration** in the convergence speed of the algorithm. The propagation model is presented in Section II. Notation of the problem and the proposed hybrid method is presented in Section III. Results are given in Section IV and conclusions are presented in Section V.

II. Propagation Model

A detailed description of the propagation model can be found in [12] and [3]. The probability of successful identification equals the probability that the instantaneous power at the tag IC is greater than its wake-up threshold. In the presence of a strong LOS path, fading is well described by a Rician probability density function:

$$f(x|\nu,\sigma) = \frac{x}{\sigma^2} e^{\left(\frac{-(x^2+\nu^2)}{2\sigma^2}\right)} I_0\left(\frac{x\nu}{\sigma^2}\right), \tag{1}$$

where ν^2 is the power of the LOS path, $2\sigma^2$ is the average power of the other contributions x is the signal's amplitude and $I_0(z)$ is the modified Bessel function of the first kind and zero order. The cumulative distribution function (cdf) is given by:

$$F_X(x|\nu,\sigma) = 1 - Q_1\left(\frac{\nu}{\sigma}, \frac{x}{\sigma}\right), \tag{2}$$

where $Q_1(a,b)$ is the Marcum Q-function. A tag is considered successfully identified if the voltage at the tag's IC is greater than its "wake-up" threshold γ. The identification-probability at a reception point is:

$$P(X \geq \gamma) = 1 - F_X(\gamma|\nu,\sigma). \tag{3}$$

Therefore, by defining ν and σ at each reception point, one calculates the desired probability for a single reader-antenna configuration. ν^2 is the power of the LOS path, while $2\sigma^2$ is the mean power of all other contributions. The latter is approximated by a closed form expression, analytically described in [12].

III. RFID Network Planning

Consider an area, where a large number of reader antennas needs to be installed, in order to provide identification performance with specific quality-constraints, e.g. all points of interest should be identified with at least 95% probability. We consider N reception points that define the points of interest of the problem (where passive tags will be located). Let A be the set of all M possible reader-antenna configurations. Each configuration is defined by the antenna-location, the radiation pattern (including polarization of the transmitted field), orientation and power. The final solution should include a subset of M, so that the desired identification-constraints for all N reception points are satisfied.

A. Notation

Let T be the set of demand identification locations and A be the set of available antenna configurations (locations, power and orientations). We define:

- B a subset of A, $B \subseteq A$, that contains the active antennas of the network,
- $|B|$ the number of active antennas in B, that is the cardinality of B,
- p_{ij} the probability of successful identification at demand-location (tag) $i \in T$, by any antenna-configuration $j \in A$.
- $p_B(i)$ the probability of successful identification at demand-location $i \in T$ by all active antennas of the network, defined in B,
- d_i the minimum acceptable probability of successful identification at demand-location $i \in T$.
- $q_B(i)$ a binary variable at demand-location $i \in T$ that equals one if the probability of successful identification of the tag is smaller than the requested threshold, given the set of active reader antennas B:

$$q_B(i) = \begin{cases} 1, & p_B(i) \leq d_i \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

- γ_i is the considered wake-up threshold at the tag's IC located in $i \in T$.
- U_B is the percentage of successfully identified demand locations of the network.

We assume that the interference problem caused by the interoperability of multiple readers in the same area using the same physical resources is handled by appropriate scheduling of transmissions in the time domain. Interfering readers should transmit in different time-slots. Furthermore, we consider a tag successfully identified, if it is identified by ***any*** of the active reader-antennas of the network. Therefore, probability p_i is given by

$$p_B(i) = 1 - \prod_{j \in B}(1 - p_{ij}). \tag{5}$$

The percentage of successfully identified tags of the network for the active antennas of set B is given by [15] (ch. 4), [12]

$$U_B = \frac{1}{N}\sum_{i \in T} p_B(i). \tag{6}$$

B. Optimization Problem

We want to minimize the number of readers, subject to the constraint that each demand location is identified with probability greater than the minimum defined for this location. Namely:

$$\min |B|, \text{subject to} \tag{7}$$

$$\sum_{i \in T} q_B(i) = 0 \tag{8}$$

C. Particle Swarm Optimization

We consider K particles. Each particle represents a set of reader-antenna locations, denoted as B_j, $j = 1, \ldots, K$, $B_j \subseteq A$, that aims to satisfy the objective function (7)-(8). All sets have the same cardinality: $|B_i| = |B_j|, i \neq j$. Within each iteration of the PSO, each particle "flies" in the problem space with a velocity vector, influenced by the specific particle's best previous experience (self-cognitive) and by the overall best experience of the entire group of particles (social-influence) [4]. As the set of active reader antennas of each particle may change after each iteration k, each set of active antennas is represented by $B_j(k)$. After each iteration, we calculate the quality factor for each particle:

$$Q_{B_j(k)} = \sum_{i \in T} q_{B_j(k)}(i), \tag{9}$$

where $q_{B_j(k)}(i)$ is defined in (4). If (9) becomes zero for any of the sets $B_j(k)$, therefore satisfying the optimization constraint of (8), the number of active reader antennas is reduced by one and the PSO starts again. If the PSO does not find a solution, such that $Q_{B_j(k)} = 0$, after a given number of iterations, the algorithm stops and the most recent solution that nulled $Q_{B_j(k)}$ is given. This represents the best found solution that satisfied (7)-(8).

1) The Optimization Loop: Let L be the number of active reader-antennas of the problem $|B_j(k)| = L$ and $X_j(k) = \begin{bmatrix} X_{j1}(k) & \cdots & X_{jL}(k) \end{bmatrix}$ the vector with the positions of the L active antennas of the j_{th} particle, during the k_{th} iteration. The position vector $X(k)$, contains the coordinates of each reader-antenna for each particle during the corresponding iteration:

$$X(k) = \begin{bmatrix} X_{11}(k) & \cdots & X_{1L}(k) \\ \vdots & \vdots & \vdots \\ X_{K1}(k) & \cdots & X_{KL}(k) \end{bmatrix} = \begin{bmatrix} X_1(k) \\ \vdots \\ X_K(k) \end{bmatrix}. \tag{10}$$

The position vector $X(k)$ changes after each iteration according to a velovity vector $V(k)$:

$$X(k+1) = X(k) + V(k),\ k \geq 0, \text{where} \tag{11}$$

$$V(k) = \begin{bmatrix} V_{11}(k) & \cdots & V_{1L}(k) \\ \vdots & \vdots & \vdots \\ V_{K1}(k) & \cdots & V_{KL}(k) \end{bmatrix} \tag{12}$$

and $V_{ji}(k)$ is the velocity of the i_{th} reader antenna of the j_{th} particle during the k_{th} iteration. During each iteration and for each particle, we calculate $Q_{B_j(k)}$, given in (9). The particle that minimized $Q_{B_j(k)}$ for the specific particle's history (after k iterations) is stored in the array $M_j(k) = \begin{bmatrix} M_{j1}(k) & \cdots & M_{jL}(k) \end{bmatrix}$, $j = 1, ..., K$. The particle that minimized $Q_{B_j(k)}$ among all particles after k iterations is stored in the array $G(k) = \begin{bmatrix} G_1(k) & \cdots & G_L(k) \end{bmatrix}$. The velocity of each element of the velocity vector (12) can now be defined as:

$$\begin{aligned} V_{ji}(k) = \omega V_{ji}(k-1) + c_1 rand^1_{ji}(k)(M_{ji}(k) - X_{ji}(k)) \\ + c_2 rand^2_{ji}(k)(G_j(k) - X_{ji}(k)), \end{aligned} \tag{13}$$

where ω is called inertia weight, c_1, c_2 are acceleration coefficients and $rand^{1,2}_{ji}$ are random numbers uniformly distributed in $[0, 1]$. After calculating the velocity of each element, the position vector for iteration $k+1$ can be updated according to (11). Successful completion of the algorithm strongly depends on the velocity update. The first part (inertia) is used to avoid particle changing velocity abruptly, the second part forces the particle to "fly" towards the best "self-cognitive" known position, while the third part towards the best overall position, found so far.

D. Proposed Hybrid PSO

We propose a new method that imitates the actions taken by a human when planning a network. A planner would typically test the performance of a given antenna configuration, identify the problematic locations and move the available antennas towards these locations. Antennas close to the problematic locations would be moved at greater distance-steps with respect to antennas away from the problematic locations, so that the final configuration would cover all volume of interest.

1) Clustering: In order to apply this concept, during each iteration of the PSO and for each particle j, we identify the coordinate-vector y_n of all locations n that do not satisfy the quality criterion set in (4). We define a set $F_j(k)$ with all demand identification locations for which $q_{B_j(k)}(n) = 1$:

$$F_j(k) = \{y_n : n \in T, q_{B_j(k)}(n) = 1\}. \tag{14}$$

Then, we partition the set $F_j(k)$ into m_j disjoint sets (clusters) $C_j(k) = \{C_{j1}(k), C_{j2}(k), \cdots, C_{jm_j}(k)\}$, so as to minimize the within-cluster sum of squares WCSS:

$$\underset{C_j(k)}{\operatorname{argmin}} \sum_{l=1}^{m} \sum_{y_n \in F_j(k)} |y_n - \mu_{jl}(k)|^2, \tag{15}$$

where $\mu_{jl}(k)$ is centroid of points in $C_{jl}(k)$, defined as the mean of the coordinates of points in the set. In order to locate the m_j centroids, we apply the "k-means" method [16].

2) Introducing the Virtual Force Velocity Vector: As soon as the centroids for each particle j during the current iteration k are determined, for each antenna of the particle, we calculate the vector with the minimum distance from the nearest centroid:

$$\begin{aligned} D_{ji}(k) = \mu_{jl_{min}}(k) - X_{ji}(k), \text{where} \\ l_{min} = \underset{l}{\operatorname{argmin}} \Big\{ \sqrt{|\mu_{jl}(k) - X_{ji}(k)|^2}, l = 1, \ldots, m_j \Big\} \end{aligned} \tag{16}$$

Then we define a new velocity vector, similar to the virtual force of the APF method, for each antenna $V^{cluster}_{ji}(k)$:

$$V^{cluster}_{ji}(k) = \frac{D_{ji}(k) a b e^{-b|D_{ji}(k)|}}{|D_{ji}(k)|}. \tag{17}$$

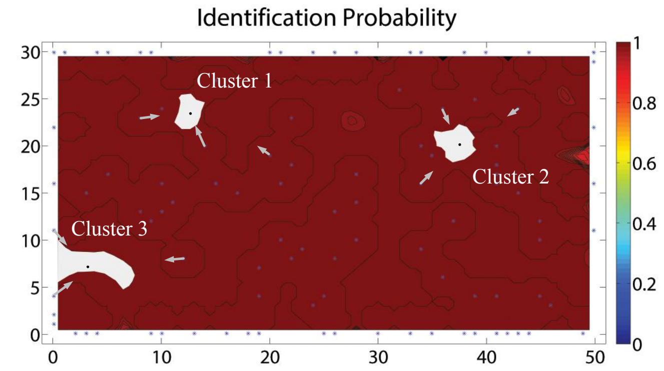

Fig. 1. Introduction of the proposed velocity vector, based on clustering of poorly identified locations.

The velocity in (17) decreases exponentially with the distance from the nearest centroid. Constants a, b should be set according to the step-distance of the available antenna-grid defined in set A and simply scale the exponential function. Recommended settings are: $a = 20 * d_{grid}$ and $b = 0.2 * d_{grid}$, where d_{grid} is the distance-step between candidate antennas of the considered grid. Finally, the velocity vector of the PSO, defined in (13) now becomes:

$$V'_{ji}(k) = \frac{w_1}{w}\omega V_{ji}(k-1) + \frac{w_2}{w}c_1 rand^1_{ji}(k)(M_{ji}(k) - X_{ji}(k)) + \frac{w_3}{w}c_2 rand^2_{ji}(k)(G_j(k) - X_{ji}(k)) + \frac{w_4}{w}V^{cluster}_{ji}(k), \quad (18)$$

where $w = \sum_i w_i$. The weights w_i size the importance of each term. Good performance was found for $w_1 = 1$, $w_2 = 0.5$, $w_3 = 0.5$, $w_4 = 1$.

An example of the proposed optimization method is presented in Fig. 1. The locations, where the identification quality threshold is not satisfied, form three clusters (shown in white). The centroids of the clusters "attract" the surrounding antennas so that the nearest ones are assigned a larger velocity.

IV. Application and Results

We consider a 50m×30m building. We assume two types of available reader antennas: i) a 7dBic circularly polarized antenna and ii) a dipole antenna. The circular antenna is employed only at the surfaces of the surrounding walls of the building, while the dipole antenna is considered at locations not attached to the wall. At each tag-location, we assume polarization diversity: a tag is successfully identified if the power at any of the three polarization axes x, y, z is greater than the wake-up threshold. The corresponding threshold is set to -15dBm and the appropriate field is substituted in (3). The candidate antenna set A comprises approximately 1500 reader-antenna configurations, evenly spaced at 1m intervals. The set of tags T to be identified comprises approximately 6000 locations evenly spaced at 0.5m intervals along the same height of 1.5m. For each antenna we calculate the probability of successful identification of all tags in T. The implemented

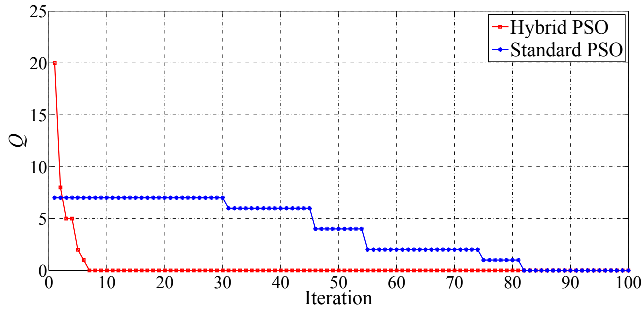

Fig. 2. Variation of quality factor Q during iterations.

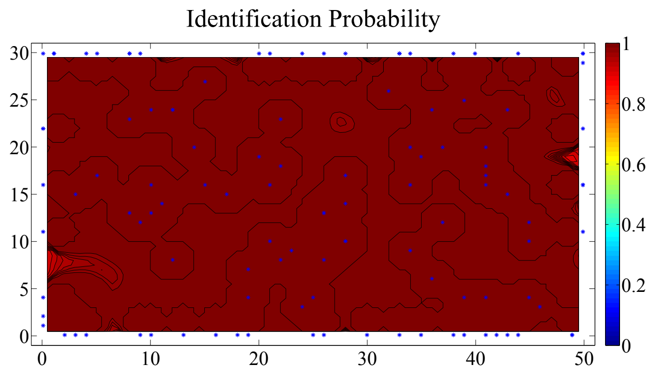

Fig. 3. Identification probability of all active antennas of the network (standard PSO).

model [12], needed only 2s per antenna-configuration to evaluate the probabilities for all locations.

The minimum acceptable probability for all locations is set to 0.9. We have considered $K = 10$ particles. We begin the process assuming a large number of antennas (300). When the quality factor Q equals zero (meaning all tags are identified with 90% probability), the number of antennas is reduced by 1. During the initialization phase, the antennas of each particle are arranged nearly uniformly in the area.

A. Application of the Proposed Hybrid Optimization Method

We have applied the proposed Hybrid PSO, where the additional velocity vector moves the antennas of each particle towards clusters of problematic locations as defined in subsection III-D. Convergence of the algorithm was greatly improved. A characteristic result is presented in Fig. 2. The evolution of the quality factor Q, defined in (9), for 112 antennas is comparatively shown by applying the standard PSO and the proposed Hybrid PSO. In the 1^{st} case, the algorithm fails to improve the solution for several iterations. In the 2^{nd} case, a better solution is found almost during each iteration. As a result, the proposed algorithm finds a solution after only 7 iterations, while the standard PSO needed 83 iterations.

The final solution of the standard PSO and the proposed algorithm are demonstrated in Figs. 3, 4, respectively. The first includes 112 antennas, while the proposed method finds

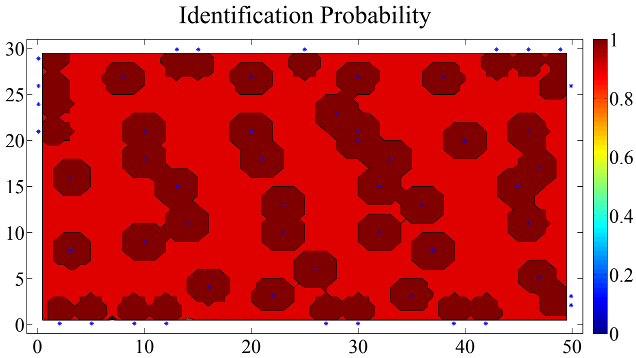

Fig. 4. Identification probability of all active antennas of the network (Proposed Hybrid PSO).

a solution with only 55 reader-antennas; a two-times improvement over the standard PSO. By altering the weights w_i in (18), we can change the importance of each velocity vector during the optimization process. We have tested the case, where $w_1 = w_2 = w_3 = 0$ and $w_4 = 1$; i.e. after each iteration, the antennas will move towards problematic locations (PSO is not applied). Worse solutions were found, because the "swarm" was trapped at local minima.

The result in Fig. 4 is indicative of the capabilities of the proposed algorithm. The algorithm can be applied for complex facilities, for non-uniform tag-locations, in 3D space, instead of a given slice along the horizon, for any reader-antenna, including beam-steering antennas and for different probability-threshold for each location.

V. Conclusion

In this paper, we put forward a hybrid Particle Swarm Optimization algorithm that includes an additional velocity vector for automated deployment of RFID networks. Taking advantage of the proposed probabilistic site-specific propagation model, the proposed algorithm evaluates the combinatorial performance of all active reader antennas; a property that is particularly important in regions, where no single reader-antenna performs well. The introduction of the proposed "virtual force" concept, where the centroids of clusters of poorly identified areas "attract" the surrounding antennas during each iteration of the standard PSO, greatly accelerated the optimization process. Furthermore, the final solution was two-times better than the standard PSO, thus reducing the installation cost accordingly. Thanks to the site-specific propagation model, the proposed optimization method can be applied for complex buildings.

Acknowledgment

This research has been co-financed by the European Union and Greek national funds through the Operational Program Competitiveness, Entrepreneurship and Innovation, under the call RESEARCH – CREATE – INNOVATE (project code:T1EDK-03032).

European Union
European Regional Development Fund
EPAnEK 2014-2020
OPERATIONAL PROGRAMME
COMPETITIVENESS ENTREPRENEURSHIP INNOVATION
Co-financed by the European Union and Greek national funds
ΕΣΠΑ 2014-2020
ανάπτυξη - εργασία - αλληλεγγύη
Partnership Agreement 2014-2020

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