Automated RFID Network Planning with Site-Specific Stochastic Modeling and Particle Swarm Optimization

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***Abstract*—In this paper, a solution for automated passive RFID network planning is proposed. The proposed scheme comprises two parts; i) a fast site specific stochastic propagation model that extracts the probabilities of successful identification for any possible reader-antenna configuration, ii) a particle swarm optimization (PSO) algorithm that selects a subset of the antenna-configurations to be installed so that a given cost function is satisfied. In contrast to prior art, the combinatorial performance of all reader antennas is evaluated at each tag location; this revealed that good identification-performance is recorded at overlapping regions, where no single reader-antenna would operate adequately. As a result, the final solution includes less equipment, reducing the cost of the network. Results presented herein demonstrate that nearly half the number of antennas are needed for the same problem, compared to prior art.**

I. Introduction

Radio Frequency Identification (RFID), as the key enabler for the "Internet of Things", continuously increases its market share, replacing traditional barcode technology and allows for the development of new applications [1]. 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 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, [2]- [7]. It has been shown in [8] that this problem is NP-complete. As a consequence, solutions are sought by employing evolutionary algorithms, e.g. [3]- [4], or particle swarm optimization algorithms (PSOs), [4]- [7].

In [3]- [7], the authors define one or more objective functions, aiming to satisfy them either concurrently by properly weighting the importance of each function, or sequentially, e.g. satisfying the most important function first. A key-element of all approaches is the considered propagation model. Since the running-time of existing computational electromagnetic methods, [9], or analytical ray-tracing, [10], is prohibitive for such estimations, simplified propagation models are considered in prior art, [3]- [7]. In all cases, except [5], a "modified" Friis equation with distance attenuation factor n ranging from 1.5 to 4 is considered. In [5], the propagation model presented in [13] is employed; the minimum reception level of the interference pattern created from the phase-sum of the direct field and the singly reflected field from the wall opposite to the antenna defines an ellipsoid as the "useful reading region". In all cases, including [5], the propagation models define a closed area/volume around the reader antenna, where successful identification is guaranteed by the corresponding antenna. A tag outside that region is not identified. This closed region is smaller than the actual area, where a tag might be successfully identified. Due to the properties of the simplified propagation-models, fading is not modeled. Furthermore, the interaction between different antennas in the total performance of the network is not handled properly; instead, each antenna is treated separately. This property could lead to non-optimal solutions in terms of cost, with more reader-antennas than needed, as demonstrated in the example of Fig. 1; in order to cover the entire building, leaving no gaps (no white areas in Fig. 1), dense deployment is carried out. Each ellipsoid or circle represents the read-region predicted by the simplified model; the shape depends on each antenna's pattern. In an effort to limit this effect in [3]- [7], overlapping coverage zones by different antennas are treated as interference (from the antennas with the weakest powers towards the antenna with the strongest power), which must be minimized in one of the defined objective functions. However, this objective cannot be satisfied together with the coverage objective.

In [10], we had shown that the interaction between different antennas of the same network can greatly improve the identification performance of the RFID network, minimizing fading effects in the identification area (and should not be considered as interference); a finding that cannot be sized in the planning approaches of prior art. We have recently proposed a site specific stochastic model, especially designed for large-scale RFID networks [11]. Initially, in [12], we demonstrated how individual propagation paths (reflected rays, direct rays, etc.), extracted from a site-specific propagation model, can be appropriately mapped to the parameters of a Rician probability density function (pdf) [14], so that *the probability* of successful identification of a passive tag for a given configuration can be calculated. Then, in [11] we proposed a site-specific stochastic model, where the aforementioned probability is estimated by the appropriate Rician cumulative distribution function (cdf) in

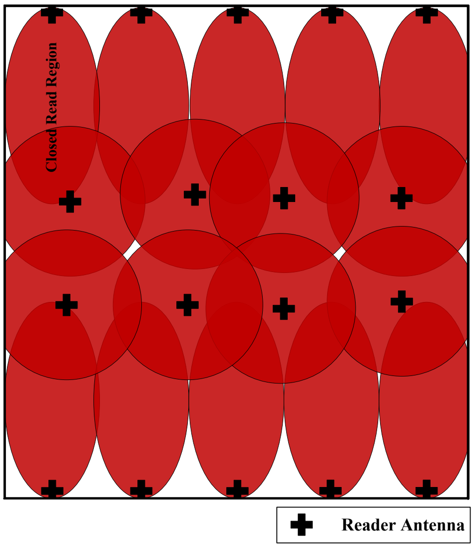

Fig. 1. Final solution includes excessive reader-antennas, because the interaction between different antennas is not included in the estimation of the identification-performance of the network.

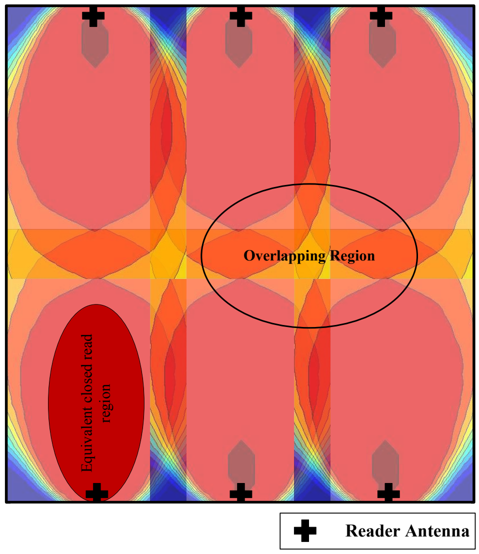

Fig. 2. The entire network's performance is evaluated, calculating the probability of successful identification by all active antennas of the network.

short running time, so that it can be implented in large-scale problems. Furthermore, we demonstrated that different Rician pdfs must be extracted for each point of interest (and not a single Rician-pdf for the entire area of interest). The model carefully considers all parameters of the problem, including the radiation pattern, geometry and materials of the surrounding walls, as well as polarization of both reader and tag antennas and calculates the desired probability. Results were verified against analytical ray-tracing estimations and measurements.

As the identification-probability from each antenna is specified, we can directly evaluate the identification-probability at each location by all operational antennas of the RFID network, assuming independence; as the real planning problem necessitates. This important property is demonstrated in Fig. 2. Due to the interaction between different reader-antennas, the desired identification performance is accomplished for locations, where no single reader antenna of the network performs well. This allows the planning-algorithm to find a solution with less equipment (smaller cost) that meets the quality criteria. In this paper we propose an automated planning method, where performance of each possible antenna-configuration is evaluated by implementing the model in [11]. Solution is found by implementing a Particle Swarm Optimization algorithm, with different objective functions than prior art. We allow different reader-antennas with overlapping identification-zones in the final solution and seek only the minimization of reader-antennas (equipment cost), under specific identification performance.

II. Propagation Model

As discussed in the introduction, we calculate the probability of successful identification of passive RFID tags in the area of interest [11]. We consider a calculations' grid and the reader's antenna at a given location. We assume that Line of Sight (LOS) conditions are satisfied for all points that might be successfully identified. This assumption is justified by the power constraints of battery-less RFID systems. The minimum power needed in the tag to operate is in the order of -18dBm, while the maximum Effective Isotropic Radiated Power (EIRP) by the reader is in the order of 35dBm in the UHF frequency band. As a consequence, in the absence of a strong LOS path, powering up the tag is improbable.

A passive RFID tag is typically cosidered successfully identified, if the power that reaches the tag is greater than its wake-up threshold, assuming that the sensitivity of the reader is small enough to receive the backscattered signal from an "awaken" tag. The proposed model can be applied for the reverse link as well, but for simplicity we consider the system forward link limited [15]. 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 succesfully 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, we can calculate the desired probability for a single reader-antenna configuration.

In [11] a prototype method to rapidly calculate the above parameters at each reception point was presented. As mentioned previously, ν^2 is the power of the LOS path. The average power of all other contributions defines $2\sigma^2$ in (1). To calculate the latter, we consider only the multiply reflected rays, assuming that diffraction and scattering in smaller objects typically results in ray-components with smaller magnitude. For the calculation of the average power of the multiply reflected rays, we consider ray-clusters that include all rays that initially bounce on the same wall, e.g. for a typical room/building, six ray clusters are considered for the six surrounding walls. Within each cluster, we consider the phases of the rays as random variables, identically and independently distributed, uniformly over $[0, 2\pi]$. Furthermore, we approximate the magnitude of the reflection coefficients of higher order terms with the magnitude of the reflection coefficient of the singly reflected ray of the specific cluster. Based on these approximations, the resulting average power from a given ray-cluster is given as:

$$P_{\hat{\eta}_0} = A\cos^2(\psi)\sum_n \frac{(|\Gamma_1^{\perp}|^2)^n}{r_n^2},$$
$$P_{\hat{\epsilon}_0} = A\sin^2(\psi)\sum_n \frac{(|\Gamma_1^{\parallel}|^2)^n}{r_n^2},\ A = \frac{\lambda^2 W_t G_t(\phi_1,\theta_1)}{(4\pi)^2}, \quad (4)$$

where $\hat{\eta}_0$, $\hat{\epsilon}_0$ are unit vectors perpendicular and parallel to the plane of incidence for the singly reflected ray of the cluster, respectively, ψ is the angle of the incident field vector with $\hat{\eta}_0$, $\Gamma_1^{\perp}$, $\Gamma_1^{\parallel}$ are the perpendicular and parallel reflection-coefficients for the singly reflected ray of the cluster, r_n is the length of the path of each ray in the cluster and $G_t(\phi_1, \theta_1)$ is the transmitting antenna gain at the direction of the singly reflected ray of the cluster. In order to apply (4), one should calculate explicitly only the 1^{st} order reflection term from the specific wall. The power along any polarization axis is calculated, by projecting the estimations to the desired axis. Details on the derivation of the probabilistic model can be found in [11]. Once ν and σ are calculated at each reception point, we can calculate the identification probability for any polarization axis by implementing (3).

Such an example is demonstrated in Figs. 3-4. The probability in (3) is calculated along three polarization axes x, y, z. Afterwards, the probability for tags' polarization diversity at each reception point is calculated. In Fig. 3, a 7dBic directional antenna is considered at $x = 9$m, $y = 0.1$m. The power at the tag should be at least -15dBm along any polarization axis (selection diversity is assumed). A similar result for a dipole reader antenna located at $x = 22$m, $y = 18$m is presented in Fig. 4.

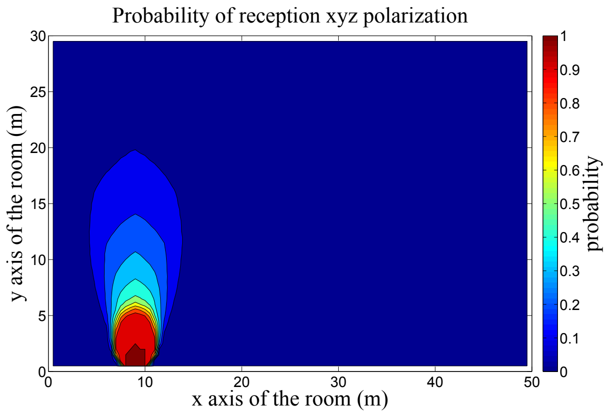

Fig. 3. Identification probability for directional reader-antenna, assuming tags' polarization diversity and γ corresponding to -15dBm.

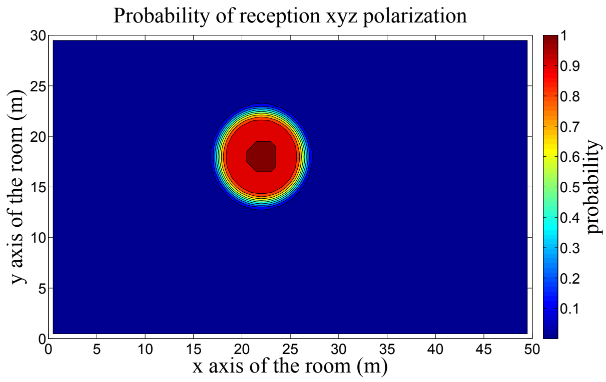

Fig. 4. Identification probability for dipole reader-antenna, assuming tags' polarization diversity and γ corresponding to -15dBm.

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. First we consider N reception points that define the points of interest of the problem (where passive tags will be located). Furthermore, 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:

- x_j a binary variable equal to one if and only if antenna-configuration $j \in A$ is selected,

$$x_j = \begin{cases} 1, & \text{antenna } j \in A \text{ is active,} \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

- p_{ij} the probability of successful identification at demand-location (tag) $i \in T$, by antenna-configuration $j \in A$.
- p_i the probability of successful identification at demand-location $i \in T$ by all active antennas of the network.
- d_i the minimum acceptable probability of successful identification at demand-location $i \in T$.
- q_i a binary variable at demand-location $i \in T$ that equals one if the probability of successful identifica-

tion of the tag is smaller than the requested threshold:

$$q_i = \begin{cases} 1, & p_i \leq d_i \\ 0, & \text{otherwise.} \end{cases} \quad (6)$$

- γ_i is the considered wake-up threshold at the tag's IC located in $i \in T$.
- U 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

$$p_i = 1 - \prod_{j \in A} (1 - p_{ij} x_j). \quad (7)$$

The percentage of successfully identified tags of the network is given by [16] (ch. 4), [11]

$$U = \frac{1}{N} \sum_{i \in T} p_i. \quad (8)$$

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:

$$\min \sum_{j \in A} x_j, \text{subject to} \quad (9)$$

$$\sum_{i \in T} q_i = 0 \quad (10)$$

As the number of antenna-configurations in A is much larger than the set of active configurations of the network, even for moderate sized problems, the optimization problem cannot be solved in reasonable time [8]. In the following section, we implement a particle swarm optimization approach to retrieve a solution to the problem.

C. Particle Swarm Optimization

In order to solve the desired planning problem, we will create a PSO algorithm [17]- [18]. The algorithm imitates the movement of organisms in a bird flock or fish school. In the PSO, we consider K particles. Each particle represents a set of reader-antenna locations that aims to satisfy the objective function (9)-(10). Within each iteration of the PSO, each particle "flies" in the problem space with a velocity. The velocity vector (speed and direction) is 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) [6]. As a consequence, the particles tend to move towards a promising area in the search space. The proposed PSO algorithm gradually reduces the number of active reader antennas, provided that (10) is satisfied. Therefore, our quality factor, used within the PSO algorithm is:

$$Q = \sum_{i \in T} q_i. \quad (11)$$

The PSO assumes a given number of active reader antennas and tries to minimise (11), as explained below. If (11) becomes zero, the number of active reader antennas is reduced and the PSO starts again. If the PSO does not find a solution, such that $Q = 0$, after a given number of iterations, the algorithm stops and the best solution that nulled Q is given. This represents the best found solution that satisfied (9)-(10).

1) The Optimization Loop: Let L be the number of active reader-antennas of the problem and $X_i(k) = [\, X_{i1} \;\; \cdots \;\; X_{iL} \,]$ the vector with the positions of the L active antennas of the i_{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:

$$X(k) = \begin{bmatrix} X_{11}(k) & \cdots & X_{1L}(k) \\ \vdots & \vdots & \vdots \\ X_{K1}(k) & \cdots & X_{KL}(k) \end{bmatrix} = \begin{bmatrix} X_1(k) \\ \vdots \\ X_K(k) \end{bmatrix}. \quad (12)$$

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

$$X(k+1) = X(k) + V(k),\ k \geq 0, \text{where} \quad (13)$$

$$V(k) = \begin{bmatrix} V_{11}(k) & \cdots & V_{1L}(k) \\ \vdots & \vdots & \vdots \\ V_{K1}(k) & \cdots & V_{KL}(k) \end{bmatrix} \quad (14)$$

and $V_{ij}(k)$ is the velocity of the j_{th} reader antenna of the i_{th} particle during the k_{th} iteration. During each iteration and for each particle, we calculate Q, given in (11). The particle that minimized Q for the specific particle's history (after k iterations) is stored in the "best-particle-vectors" array $PB_i(k) = [\, PB_{i1}(k) \;\; \cdots \;\; PB_{iL}(k) \,]$, $i = 1, ..., K$. The particle that minimized Q among all particles after k iterations is stored in the "global-best-vector" array $GB(k) = [\, GB_1(k) \;\; \cdots \;\; GB_L(k) \,]$. The velocity of each element of the velocity vector (14) can now be defined as:

$$V_{ij}(k) = \omega \times V_{ij}(k-1) + c_1 \times rand^1_{ij}(k) \times (PB_{ij}(k) - X_{ij}(k)) + c_2 \times rand^2_{ij}(k) \times (GB_j(k) - X_{ij}(k)), \quad (15)$$

where ω is called inertia weight, c_1, c_2 are acceleration coefficients and $rand^{1,2}_{ij}$ 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 (13). 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.

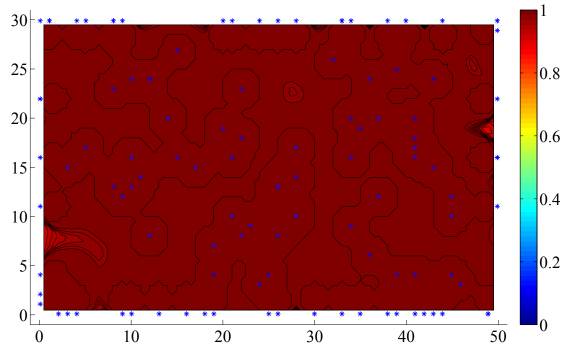

Fig. 5. Identification probability of all active antennas of the network.

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. Characteristic probability results from each antenna were presented in Figs. 3-4. 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 model [11], needed only 2s per antenna-configuration to evaluate the probabilities for all locations; a time that can be significantly reduced if the estimations are confined in a given area around each antenna (because outside this area the probability is almost 0 as shown Figs. 3-4).

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. 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. The following parameters were selected for the PSO: $\omega = 0.5$, $c_1 = c_2 = 2$. We have considered a maximum number of 300 iterations. The evolution of the quality factor Q, defined in (11), during an execution of the PSO is shown in Fig. 6. The corresponding "best particle" is shown in Fig. 5, where the locations of the reader-antennas are marked with "*" and the identification-probability of the entire network in all locations is demonstrated.

The results in Figs. 5-6 are indicative of the capabilities of the proposed algorithm. The algortihm 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.

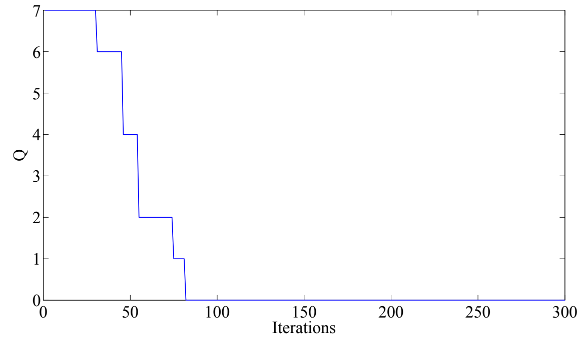

Fig. 6. Variation of quality factor Q during iterations.

A. Comparison with Prior Art

As discussed in the introduction, in prior art, [3]- [7], the propagation models define a closed volume around the antenna, where successful identification is guaranteed. The identification performance gains, due to the interaction between different antennas are not considered. Hence each tag must belong to the closed volume of at least one antenna, in order to be considered successfully identified. In order to compare the proposed model with prior art, we must map the extracted Rician pdfs (for each tag location) to the equivalent received power level that ensures the same identification probability p_i at each location i. Therefore, we wish to calculate the minimum received level P_i at each location that ensures identification probablity p_i. Let X denote the received level. For the probability, we have:

$$P(X \geq P_i) = p_i \Leftrightarrow 1 - P(X \leq P_i) = p_i \Leftrightarrow \\ \Leftrightarrow P(X \leq P_i) = 1 - p_i \quad (16)$$

Since the Rician pdf at each location i is defined in (2), we calculate P_i from the inverse cumulative distribution (quantile) function F_x^{-1} at $1 - p_i$:

$$P_i = F_x^{-1}(1 - p_i) \quad (17)$$

If the calculated level P_i at location i is greater than the tag's threshold γ_i, then the quality criterion defined in (6) is satisfied and $q_i = 0$. Such an example is demonstrated in Fig. 7, where $p_i = 0.9$ for all points of interest. By applying (17) we calculate the minimum power level that ensures idenitifcation percentage greater or equal to 90% and demonstrate these values to the minimum reception tag's threshold of -15dBm. By comparing the plot of Fig. 7 with the corresponding probability plot presented in Fig. 3 (same antenna and same Rician pdfs), the coloured region of the power-plot matches the region with identification probability equal or greater than 0.9, as it should.

Since we have mapped the Rician pdfs of the proposed model to the equivalent received power, we can apply the PSO algorithms proposed in [3]- [7]. The optimization problem is that all tags should be successfully identified, i.e. the power P_i by at least one antenna should be greater than the minimum threshold. If two or more particles share the same identification performance, the particle with the smaller total interference (least overlapping zones among different antennas) is selected as the best particle, as proposed in [6]. When all tags are

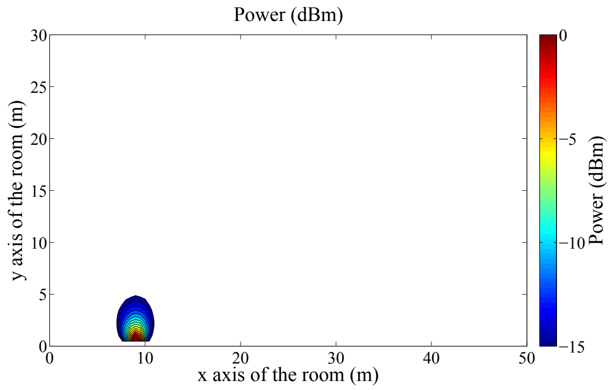

Fig. 7. Power level that ensures 90% successful identification for directional reader-antenna, assuming tags' polarization diversity and γ corresponding to -15dBm.

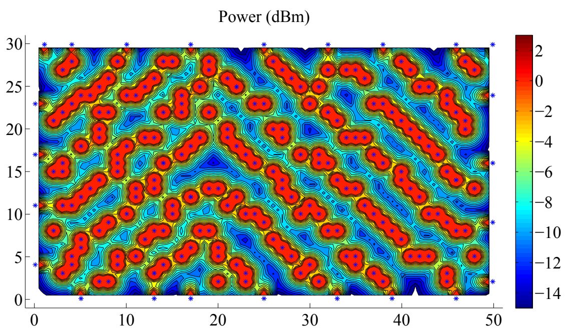

Fig. 8. Minimum received power for 90% of time of all active antennas of the network.

successfully identified, the number of antennas is reduced by 1.

The solution extracted by this algorithm includes 218 reader-antennas. The final installation of the antennas is demonstrated in Fig. 8. For the same problem, the solution extracted by the proposed model includes only 108 reader antennas (see Fig. 5), almost half the number of antennas of the models in prior-art. The reason for this large improvement is the great performance gain accomplished in the overlapping regions of different antennas that is suitably defined in (7). In simple words, in overlapping regions (see Figs. 1-2) where no single-antenna matches the quality criteria, the combination of all antennas results in excellent performance.

V. Conclusion

In this paper, we presented a Particle Swarm Optimization algorithm for automated RFID network planning. In constrast to prior art, 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. Further work can be carried out towards accelerating the optimization proccess.

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