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Optimization of a Radio Frequency Energy Harvesting Device

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Abstract — **This paper proposes the optimized design of a wireless energy harvesting device (EHD), by means of a recently developed evolutionary optimization method. This procedure is developed in order to increase the transfer efficiency and the robustness of the coupling, with the aim of minimizing the average power loss, and to increase the lifetime of a wireless sensor network by scavenging RF energy available in the environment.**

Keywords: *wireless power transfer, energy harvesting, evolutionary optimization, fractal antenna.*

I. Introduction

In the last five years wireless sensor networks have been attracting considerable research attention for a wide range of applications, but they still present significant network communication challenges, essentially involving the use of large numbers of resource-constrained nodes operating unattended and exposed to potential local failures. In order to maximize the network lifespan, suitable energy harvesting techniques can be developed [1].

Energy harvesting for powering ubiquitously deployed sensor networks and mobile electronics is a growing field of study [2,3]. Recent developments in microcontroller, radio transceiver, and energy harvesting device (EHD) will permit sensor nodes to operate indefinitely from power scavenged from their environment. Typically, EHDs can scavenge small amount of energy from power from human activity or environment heat, light, vibrations or electromagnetic (EM) fields [4].

II. Application

Sensor networks application in different technological areas is increasingly growing and offers a rich domain of active research. These complex systems use technologies essentially from sensing, communication, and computing fields and combine at the same time many design issues of wireless communication and mobile computing. They still present significant system challenges since the network utilizes large numbers of sensors operating essentially as resource-constrained nodes and exposed to potential failures. Advances in sensor production technologies have made possible manufacturing very compact and autonomous sensor nodes, each containing one or more sensor devices, computation and communication capabilities, and limited power supply, promising for WSNs better coverage, higher resolution, fault tolerance, and robustness. Networking the sensors can facilitate the transmission and dissemination of the measured parameters to some collector sites at which the information is further processed for decision-making purposes. The distributed nature of the network makes it even more attractive in military and other sensitive applications. Performing the processing at the source can dramatically reduce the computational cost of networking and management; therefore, WSN organization should be autonomously performed with a minimum of human interference.

Even if nowadays analog and digital technologies make it possible to develop cheap, small, and low-power sensor nodes, the challenge is to make the sensor network completely energy autonomous. Minimizing energy consumption certainly is a critical aspect when designing sensor network protocols and algorithms. Since sensor nodes are equipped with small and very limited batteries, it is crucial for the network to be energy efficient in order to maximize network lifetime. Recent power management developments enable battery-powered devices to live longer, by using dynamic optimization of voltage and clock rate and suitable wake-up procedures to keep the electronics in idle state most of the time thus consuming low power.

Moreover, in conventional sensor networks suitable algorithms have been developed in order to conserve energy. However, exploiting energy resources already available in the device's environment offers an additional power source

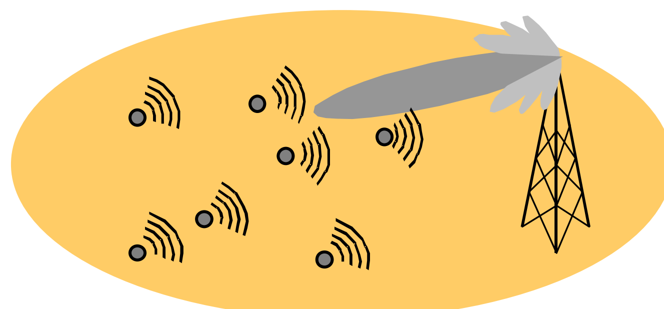

Figure 1. Wireless sensor network with passively powered sensors.

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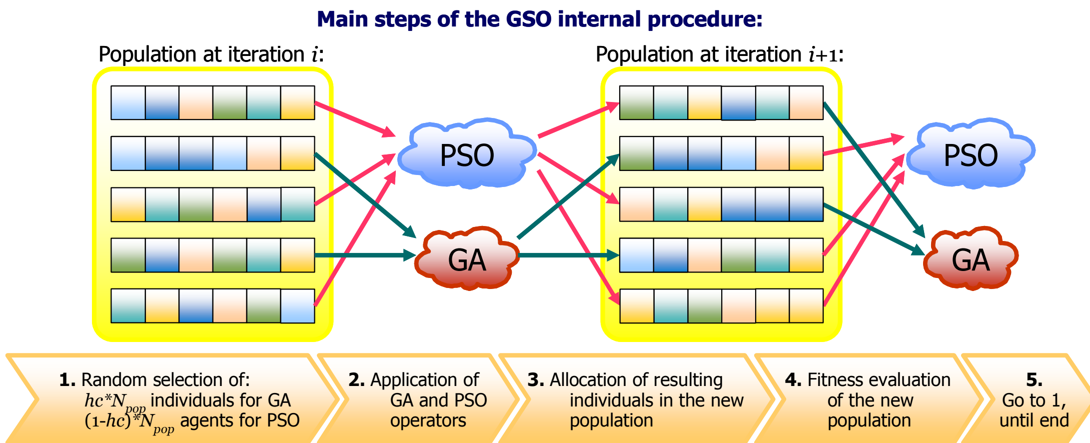

Figure 2. Flow chart of main operations performed by the GSO algorithm.

potentially unlimited.

Harvesting approaches that scavenge energy from waste heat or vibration are quite common [4]. Recently, the availability of wireless standards for a huge number of applications, from mobile phones to always-on WLAN devices shifted the attention on the extraction of energy from EM fields in the RF band [5], as shown in Figure 1. Moreover, in some cases EM waves propagation is not desirable [6] and harvesting could be used to mitigate this unwanted effect.

In such harvesting system, the RF energy available power density is very low, since EM field energy drops off rapidly as propagation distance increases [7,8]. In particular, the electric field and power density drop off at the rate of $1/r^2$, where r is the distance from the radiating source. It is therefore critical that the power conversion circuit operate at very low power to achieve longer operating distance.

In the antenna community several papers have been published on this subject in the past few years [9,10], in fact, antenna shape, matching network and rectification circuits for such a system must be optimized to improve the overall energy exploitation.

III. Antenna Optimization Procedure

In order to define an automated design process of the considered antenna for WPT, an optimization procedure has been considered. In recent years, in fact, several numerical optimization techniques have been developed and widely applied to the design of electromagnetic devices [11].

Traditional approaches, such as Newton-based ones, are related to gradient descent and they are usually local algorithms. Given the large number of variables, and the discontinuity of parameters, it is generally difficult to use these traditional optimization methods to find the best solution of complex problems.

Evolutionary techniques are based on global search approaches and they can overcome these drawbacks and face nonlinear and discontinuous problems, with a great number of variables. In fact they apply an indirect synthesis, by evolving the parameters of interest towards an optimal solution; this means that one can control the behavior of the resulting devices, through a properly defined fitness function that puts constrains on the resulting performances.

Among the main evolutionary optimization approaches it is worth mentioning the Genetic Algorithm (GA) and the Particle Swarm Optimization (PSO).

In GA, each individual of the population encodes the parameters to be tuned and therefore it represents a possible solution to the problem. For each individual a fitness function is therefore evaluated and a score is assigned. GA simulate the natural evolution, adopting pseudo-biological operators such as selection, crossover and mutation to improve the fitness score associated to each individual.

In the PSO, the position of each particle represents a solution of the problem. Particles are moved in the domain of the problem being attracted by both the position of their best past performance and the position of the global best performance of the whole swarm.

These algorithms are iterative techniques with strong stochastic bases and consequently their performances are evaluated in terms of speed of convergence. The use of these techniques, requiring a relevant number of the fitness function evaluations, needs particular care if, as in this case, the cost function is computationally expensive.

Therefore these approaches must guarantee exploration of the solution domain to avoid premature convergence to local optima and exploitation of the results to concentrate the search effort and to reduce the number of requested fitness function evaluations.

Previous comparisons of GA and PSO [12] confirmed the typical application-driven performances of any single technique. In particular PSO seems to have a convergence rate faster than GA early in the run, but often it is outperformed by GA for long simulation runs.

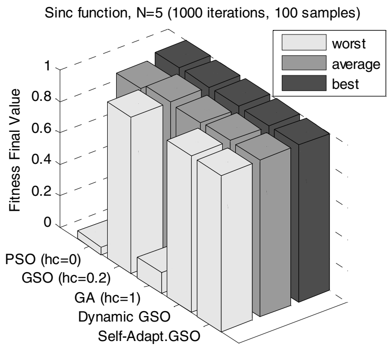

Figure 3. Final values of the *sinc* function optimization with 5 variables obtained with different hybridization strategies (average results over 100 trials).

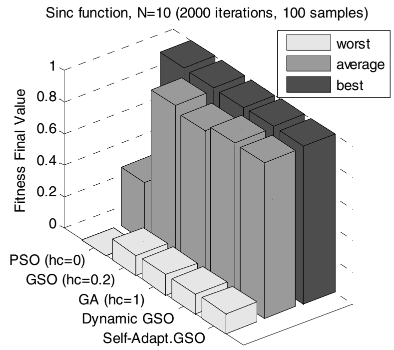

Figure 4. Final values of the *sinc* function optimization with 10 variables obtained with different hybridization strategies (average results over 100 trials).

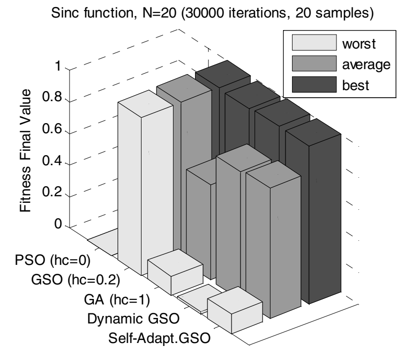

Figure 5. Final values of the *sinc* function optimization with 20 variables obtained with different hybridization strategies (average results over 100 trials).

In this work, a recently developed hybrid technique, named Genetic Swarm Optimization (GSO), is used. Its basic concepts are presented in [12] and clearly summarized in Figure 2: in every iteration the population is randomly divided into two parts which are evolved with GA and PSO operators respectively. The fitness of the newly generated individuals is evaluated and they are recombined in the updated population which is again divided into two parts in the next iteration for the next run of genetic or particle swarm operators. The driving parameter of GSO algorithm is the hybridization coefficient hc, that simply indicates the percentage of population evolved with GA in each iteration; hc value can be static or self-adaptive (as detailed in [12]) to suitably combine in the most effective way the properties of GA and PSO.

Several comparative studies over different optimization tasks have shown the effectiveness of GSO in exploring the problem hyperspace, especially for the optimization of large domain objective functions. In fact, as results reported in Figures 3 – 5 show, it seems that the improvements introduced by the hybridization are increasing with the dimension of the problem to be optimized: if we consider the optimization of the well-known N-dimensional sinc function, for N=5 average performances of all the considered methods (including GA and PSO, for comparison) are almost the same, although the traditional methods sometimes fails in finding the optimal value, as shown by the bar indicating the worst performance (over 100 independent trials) in Figure 3. When N=10, the average performances of GSO are slightly better than GA and significantly better than PSO (Figure 4), while, for N=20, the improvement introduced by the hybridization is not negligible, since just the different GSO implementations are able to locate the optimal value, as shown by the bar indicating the best performance in Figure 5, while, for the considered number of iterations, neither GA nor PSO are able to get the optimal value in 100 trials and their average performance is lower than GSO' one. Moreover, the best performance is here obtained using hc=0.2, since this value has been found to be the optimal for this kind of problem, but anyway the adaptive strategies are still better than the traditional techniques. For these reasons, GSO has been already successfully applied to the optimization of antennas, wireless systems and energy harvesting devices [13], usually allowing the reduction of the number of iterations, and thus the computational effort, requested to optimize complex electromagnetic problems.

IV. Simulation and Numerical Results

In order to design an optimized antenna for wireless energy transfer, preliminary analyses have been conducted in particular on the optimization of the antenna shape, considering the fractal geometry reported in Figure 6. The choice of such geometry is due to the need of reducing antenna dimension, as described in [14].

The considered case study of an EHD sensor node operating from RF energy, takes into account the design of the matching network too, as reported in Figure 7. In particular, here simulations are conducted on an equivalent model based on two

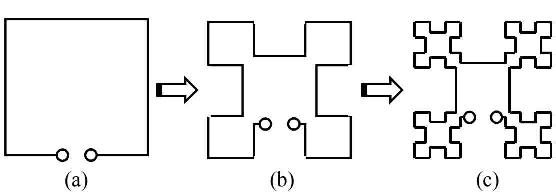

Figure 6. The considered fractal antenna shape to be optimized.

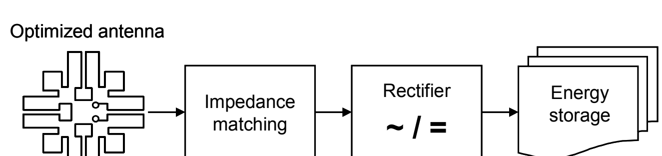

Figure 7. Schematic of the considered RF energy harvesting device.

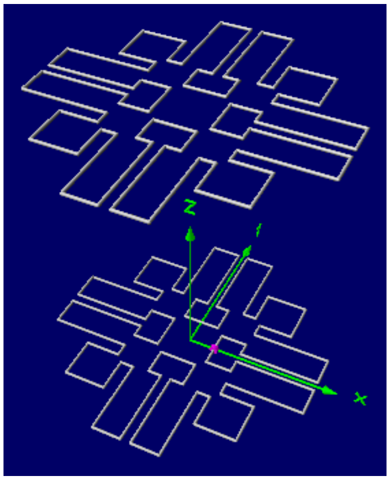

Figure 8. Case study analysed with NEC (optimised configuration).

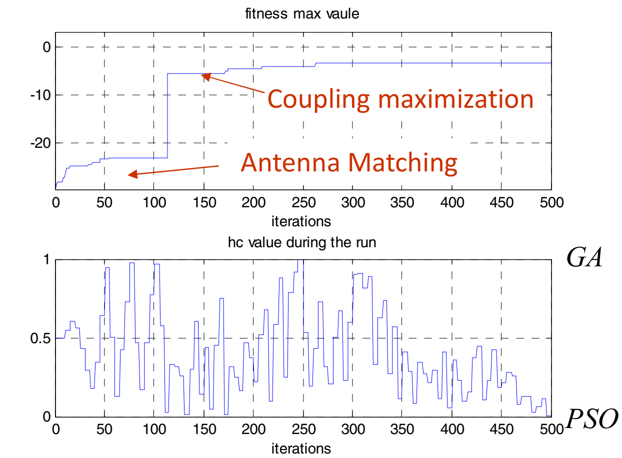

Figure 9. Evolution of fitness score and hc values during iterations.

identical fractal planar antennas separated by an air gap, as reported in Figure 8.

Simulations were done using the freely available 4NEC2 antenna modeller [15], interactively called by the presented optimization procedure, in order to evaluate the coupling performances of the proposed antenna geometries. The aim of the analysis was to design the geometry in order to maximize the coupling versus the displacement and to minimise the antenna footprint.

The implemented model decodes the information provided by GSO into geometrical dimensions to assign to the antenna design; afterwards, it analyses the new configuration and evaluates the feasibility, the return loss S_{11} and the transmission coefficient S_{21} of the wireless system.

In particular, in order to maximize the energy transferred it is desirable to have the antenna matched in the frequency band of interest, thus minimizing S_{11}, that is the return loss at port 1. Moreover, when the antenna is matched, it is necessary to maximise the coupling performance S_{21}.

To reach out these different objectives, which must be sequentially satisfied, authors chose a multi-objective approach called ε-constrained method [16] by adopting thresholds for the fitness function in order to identify different phases into the fitness score evaluation.

In the first stage, fitness score value f is then defined as:

$$f = -50 \quad \text{(until geometry is feasible)}$$

in order to penalize unfeasible solutions; when geometrical feasibility is obtained, f is computed as:

$$f = -30 - S_{11} \qquad (\text{if } S_{11} > \text{-10 dB})$$

to minimize return loss at the considered working frequency. Finally, when return loss has reached the desired value:

$$f = S_{21} \qquad (\text{if } S_{11} < \text{-10 dB})$$

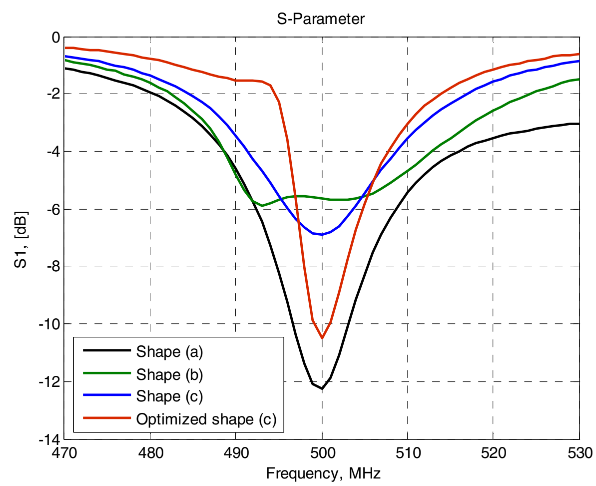

Figure 10. Size comparison of analyzed geometries.

in order to maximize antenna matching at the considered working frequency.

Here, the optimization procedure considers a population of 10 candidate solutions per iteration and it runs for 500 iterations, thus leading to 5000 cost function calls. Self-adaptive *hc* is considered to maximise the GSO performances, as reported in [12].

A sample evolution of fitness value is reported in Figure 9, where the stage 2 and 3 are highlighted. Moreover, in the same figure the *hc* value during iterations is reported, showing that, in this particular case, self-adaptive GSO goes towards an almost exclusive application of PSO operators.

Numerical results of the optimization are reported in Figure 10. In particular, only (a) and the optimized (c) shapes are matched; moreover, the size of the antenna is significantly minimised by the optimized (c) shape, whose footprint is about half of (a).

V. Conclusions

In this paper the characterization of energy devices for wireless sensor nodes has been presented and their use in simulation and deployment outlined. In particular, a novel antenna with optimized fractal geometry has been proposed for application in WPT devices.

The presented optimization approach is based on GSO algorithm, a recently developed hybrid evolutionary method. The design procedure is built in order to increase the transfer efficiency and the robustness of the coupling, with the aim of minimizing the average power loss. Reported numerical results proved the effectiveness of the proposed optimization procedure.

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