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Research Article

A Genetic QoS-Aware Routing Protocol for the Smart Electricity Networks

Agustin Zaballos, David Vernet, and Josep M. Selga

Computer Engineering Department, La Salle Engineering, University Ramon Llull (URL), 08022 Barcelona, Spain

Correspondence should be addressed to Agustin Zaballos; zaballos@salle.url.edu

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This paper presents a QoS-aware routing protocol suitable for distribution of smart electricity grids based on heterogeneous machine to machine communications. The distribution Smart Grid needs high performance communication networks capable of handling QoS, an issue that is addressed by the present paper. The proposed algorithm is a merger between a genetic algorithm (GA) and Ticket-Based Routing (TBR), which is an on-demand routing protocol for ad hoc networks that provide quality of service. A suitable parameterization of the GA parameters is needed in order to use this protocol in the coming Smart Grid networks. The resulting routing protocol, named genetic algorithm with TBR algorithm for Smart Grids (GATAS), is an adapted intelligent evolution of the TBR. The performance of TBR has been improved by reducing the overhead of routing packets in the network and by minimizing the communication latency due to its on-demand behavior. Experimental evidence indicates that the likelihood of finding the optimum route using multiobjective dynamic metrics increases when the genetic algorithm is applied. In this paper, the main simulation results on the parameterization carried out are discussed, and the proposed attributes of the GA are described.

1. Introduction

The future of electrical utilities walks hand in hand with Smart Grids and their advantages. Smart Grids will save energy and will cope better with the unpredictable renewable energy supplies [1]. At present, utilities have to be prepared to face the increasing needs of their telecommunication infrastructures. In fact, one of the main challenges of the Smart Grid is to redesign the architecture of its communication network [2, 3]. The current utility grid scheme is relatively easy to operate, but the Smart Grid is much more complex. Its architecture is based on a decentralized scheme with elements logically identified but not geographically located. Future Smart Grids will manage great amounts of real-time information through a data network and will collect information from Intelligent Electronic Devices (IEDs) established for control purposes. This kind of data network is not exempt from the growing needs of quality of service (QoS) [4, 5]. Smart Grids are expected to face a drastic increase in information demand, communication, and various data such as voice, data, image, video, and multimedia communications, which will all have to be accessed anywhere and at any time inside an M2M architecture [6, 7].

This work deals with the issues of utmost importance to achieve QoS-aware routing in wireless and wired sensor networks based on a genetic algorithm for the sensor networks of Smart Grids. A sensor network consists of distributed sensors that cooperatively monitor physical or environmental conditions. Those sensor nodes can be located anywhere in the network and form an ad hoc network, which does not require a communication infrastructure. In this environment, sensor networks must dynamically provide the necessary QoS depending on the type of information transmitted by sensor nodes in a multihop topology.

This paper presents a new algorithm that copes with these necessities. The genetic algorithm with TBR algorithm for Smart Grids (GATAS) evolves from an ad hoc QoS-aware routing protocol but uses a genetic algorithm (GA) [8, 9] to reduce the amount of routing traffic. The object of this paper is to propose a suitable parameterized GA integrated into a QoS-aware routing protocol for the Smart Grid ad hoc network. A QoS routing selects paths based on several QoS metrics to satisfy specific requirements. This new routing protocol has been simulated using OPNET Modeler [10] in Smart Grid related scenarios [11] under the umbrella of the European project INTEGRIS [11]. The interdisciplinary project INTEGRIS addresses the development of an ICT infrastructure to handle the Smart Grid requirements. Thoroughly, INTEGRIS takes benefit from the profiles variety of its members and tackles the Smart Grid domain by proposing a global solution that considers (1) the QoS-aware communication network, (2) the ICT security issues, (3) the storage and distributed computation, and (4) a cognitive system as a self-containing block.

This paper is organized as follows. Section 2 briefly describes routing mechanisms for ad hoc networks and provides a general description of the network model used. Section 3 describes the fundamental topics involved in the work carried out and it also covers all the important design issues of our genetic QoS-aware ad hoc routing protocol for Smart Grid access networks. Section 4 introduces the characteristics of modeled routing nodes and simulation scenarios for the analysis and outlines the results obtained. Finally, Section 5 presents the conclusions of the paper.

2. Routing for Smart Grid's Data Network

Smart Grids will manage lots of real-time information through a data network, and they will collect information for control purposes from established IEDs. Smart Grid network control and monitoring are very important features in order to provide continuity [5, 12], QoS [4, 13], and security [14–16]. The future Smart Grid must be distinguished by self-healing and automation. Actually, international organizations, governments, utilities, and standardization organizations are becoming aware that the grid needs a modernization [3, 5].

Due to these circumstances, Smart Grid will be supported by highly heterogeneous data network with strict QoS constraints depending on the Smart Grid service to provide [3]. Therefore, one of the most important specifications required for Smart Grids is that regarding their communications. A framework for management of end-to-end QoS for all communications in the grid will be a must in the future [4, 7] and this specificity is something that is directly addressed by the proposal made in the paper. In fact, a suitable communication infrastructure increases the efficiency of the electric system to a much greater extent than automation without communication capacities could ever increase it.

There are several aspects that must be defined to obtain an algorithm that could be implemented in a real Smart Grid such as the detection of neighbors, the hierarchy of the network, the definition of which synchronization mechanism is used, the addressable elements in the network, or the address scheme used by the protocol to identify the nodes in the network [17, 18]. Furthermore, if the protocol is oriented to provide QoS, additional aspects have to be established, such as the QoS metric, the specification of the protocol to minimize the amount of bandwidth needed, and the load balancing scheme [4, 12].

Ad hoc network among objects is built and every sensor node may need to transmit information to other sensor nodes and not only to the center node. If the network topology changes dynamically due to mobility and if the state information is inherently imprecise, the routing protocol must be optimized for ad hoc networking. Even if the network is wired or stationary, the network topology may change because of power network changes or degradation of channel characteristics, especially in the case of Power Line Communications (PLC) and also in the case of radio systems using common frequency bands. The main goals of a routing protocol for Smart Grids are simplicity, scalability, and energy efficiency. At present, topology changes due to node mobility are infrequent as sensor nodes are stationary in most applications [12, 17, 19].

2.1. Related Work. A routing protocol consists of two basic tasks: it has to collect the state information of the network and to keep it up to date. This paper is focused on the analysis of this first task inside the ad hoc network of Smart Grids and leaves the path repair functions for further study. Many alternative solutions have been proposed and analyzed to solve the need for a routing algorithm in ad hoc networks. The main features of well-known ad hoc protocols have been studied in depth [20].

In recent years, routing optimization in data networks has received considerable attention. There are several GAs in the literature that address different routing problems, such as multicasting routing problem [21], traffic engineering based on link weight optimization [22], or shortest path routing problem without providing QoS [23, 24]. Some of them are applied in a non-real-time background mode [23]. Far from the supposed full cooperation of the participating communication nodes, game theory has attracted the interest of researchers in the field of routing as well in order to monitor possible conflicting interests between communication domains [25]. Although the findings of these studies are relevant, those approaches are beyond the scope of this paper.

Recently, routing in Wireless Sensor Networks (WSNs) has been recognized as an important research area and much work has been carried out. As a result, a great number of studies have discussed the application issues of evolutionary computation techniques [26], clustering [27], and data mining [28] in this kind of networks. Some of them will be referenced along this paper. A survey of the main approaches to the application of evolutionary techniques in WSNs can be found in [29]. Related fields of knowledge worth to mention are those of Particle Swarm Optimization (PSO) and ant routing algorithms [30] that are similar to our proposal in that they use probes that explore the space but that differ in essential aspects such as the randomness of PSO versus the flooding-like nature of our proposal (GATAS).

To the best of our knowledge, our approach is the first real-time integration of a genetic algorithm with both routing parts: the routing algebra and the routing distribution mechanism for QoS-aware networks that focus on the Smart Grids necessities on QoS. An exhaustive study using multiple simulations to determine the routing multipath algorithm with the most adequate QoS behavior for High Voltage (HV) segments has been carried out in [18]. In this highly meshed network environment, where the communication devices are very powerful, the main difficulty comes from improving the QoS behavior of the existing widely spread commercial routing protocols [13, 19]. However, the idea of designing a routing protocol appropriate for another segment of Smart Grids (medium and low voltage) is presented in this paper, in which routing protocols must operate under a set of constraints that traditional protocols do not typically consider. In this sense and given the similarities between Smart Grid networks and sensor networks, it is interesting to consider carefully the work done in the field of sensor networks.

Although there are many academic papers and well-known routing protocol implementations available based on ad hoc networks, studies and demonstrations carried out in [11, 31] formally discard all these protocols since they do not meet the minimum criteria needed for Low Power and Lossy Networks (LLNs) that are a class of networks in which both the routers and their interconnections are constrained [31]. If a protocol cannot meet these minimum criteria, then it cannot be used in several major Smart Grid application domains, and it is therefore unlikely to be a good candidate for use within a broader scope.

2.2. Network Model. In this section, the network model and the notation used for the routing algebra and policies are described. This notation is used to formally define the routing protocol behavior of GATAS, and it is based on Sobrinho's routing algebra [32]. An algebraic approach is very useful to both understand existing protocols and to explore the design space of future Internet routing protocols. The routing policy defines the elements used by the routing protocol to carry out the routing process (1). The routing policy (RP) is formed by

$$\mathrm{RP} = \langle \Sigma, \oplus, L, \preccurlyeq \rangle. \quad (1)$$

Each element of this array (1) is defined in Table 1. Based on this representation, we propose the following model of a network, where vertex j is the destination and vertex i the origin of routing information (Table 2). The proposed notation is crucial for the protocol specification in order to define the information used and stored by the routing protocol. The objective is to avoid any confusion when different routing schemes and metrics are defined at a point in the future.

Table 1: Elements of the routing policy (RP).

Element	Description
Σ	It is the cost associated with a path, and it is known as the signature of the path.
$\bigoplus$	It defines the way to add a link cost to a path and to calculate the total cost. It is known as the metric operator.
L	It represents the cost associated with a link, and it is known as the label of the link.
$\preccurlyeq$	It is the precedence relationship, and it is used to decide which path is the best choice.

3. Description of the Proposal

3.1. Underlying QoS Routing Protocol Description. GATAS algorithm is based on a network layer on-demand routing algorithm known as Ticket-Based Routing (TBR) [33]. A ticket-based probing algorithm is an imprecise information model used to find a QoS-aware routing path in ad hoc networks. TBR is very interesting for our purposes as maintaining a consistent route table in Smart Grids has become increasingly challenging due to the number of nodes whose information has to be consistent and also because of the unpredictable changes in the actual topology mentioned in Section 2. It is often impossible to know a priori what kind of environment the protocol will find itself in. A QoS routing algorithm is, after all, a complex optimization problem. Therefore and in order to solve this complex problem, the use of one of the best known techniques that has proved successful in these matters is proposed: a genetic algorithm. We evolve a QoS routing protocol using an artificial intelligent technique, and, for this purpose, reactive protocols are the most suitable kind of algorithms [20].

In the TBR routing protocol, the source node issues a certain number of tickets and sends these tickets in several probe packets to find a QoS feasible path. Each probe packet carries one or more tickets. This distributed QoS routing protocol probes multiple paths in parallel. The number of multiple paths searched is limited by the number of tickets issued by the source node in all the sent probe packets. State information maintained at intermediate nodes is used for more accurate route probing. If the available state information is not precise or if the QoS requirements are very stringent, more tickets are issued in order to improve the chances of finding a feasible path. In each probe, the probe state (signature's path and label's links) is recorded, including the path, the accumulated delay, and the accumulated cost of the path.

Figures 1 and 2 show a dialog example of the TBR mechanism as used by GATAS routing protocol. When source *Node 1* wants to find a path with some QoS requirements to the destination *Node 5*, it generates n tickets. Then, it has to distribute them among different probes delivered to every neighbor. In this example, *Node 1* only has one direct neighbor. The followed path by the probe $S_{n,p}$ is depicted in Figure 1 where the subindex n is the number of remaining probe's tickets and the sub-index p is the type of probe (probe request p or probe response r). When a probing message arrives at a neighbor, it may be split into multiple probes and forwarded again. The neighbor *Node 2* generates, in this example, two probes and distributes n tickets between its two neighbors (x tickets to *Node 4* and y tickets to *Node 3*). Each child probe will contain a subset of tickets from its parent. A probing message has to contain at least one ticket. In this way, when using a one-ticket probe, the node is not able to continue the splitting process any further, and the node can only forward it to one neighbor. When one probe arrives at the destination, the recorded path's signature is sent to the origin within a response probe (response probes $S_{y,r}$ and $S_{x,r}$ in Figure 2).

The study presented in this paper is focused on network level analysis (level 3). So, it is assumed that a link-level protocol assures that every node knows its neighbors, which

Table 2: Routing algebra notation.

Element	Description
i	It represents the origin node.
k	It represents a neighbor of node i, which has sent a routing advertisement to node i.
j	It represents the advertised destination of the routing information received.
λ_{ik}	It is the cost of the link from node i to node k.
σ_{kj}	It is the cost of the path from node k to node j advertised by node k.
$\widehat{\sigma}^{i}_{kj}$	It stands for the estimated cost of the path from node k to node j stored on the routing table of node i.
$\widehat{\sigma}^{i}_{ikj}$	It stands for the estimated cost of the path from node i to node j through the neighbor k stored in the routing table of node i.
$\widehat{\sigma}^{k}_{ij}$	It is the cost estimated of the path from node i to node j that node i guesses that is known by node k.
S_{ij}	It is a set of all the neighbor nodes of node i that are feasible successors to node j.
N_i	It is a set of all the neighbor nodes of node i.

Estimated values are the information received from the neighbors that can be potentially outdated due to network changes that have not yet been notified, as the routing protocol has not converged.

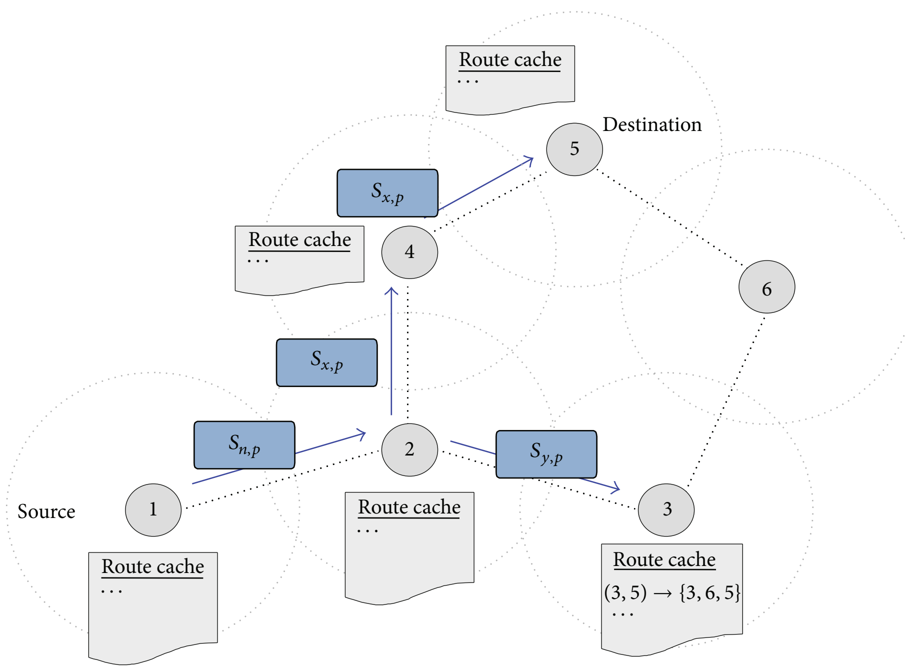

Figure 1: New search of a path (probes sending).

implies that a node detects within a finite time the existence of a new node or the loss of connectivity with a neighbor and all packets transmitted over an operational link are received correctly and in proper sequence within a finite time.

The study made in [31] discards all the analyzed ad hoc routing protocols, but it does not analyze TBR-based proposals, and, in fact, TBR and GATAS do not easily fit into any of the analyzed routing protocols. Baseline TBR table size is a function of the number of communicating pairs in the network, scaling with O (*Destinations*). As explained in [31], this is acceptable, and so TBR would pass the routing state criterion defined in [14]. As an on-demand protocol, TBR does not generate any traffic until data is sent; therefore, control and loss traffic is correlated with the data and so it receives a pass for the control traffic criterion. Furthermore, TBR does not fail the link/node cost criterion because any QoS-aware metric can be used, and the router can indicate its willingness to route a packet to a destination.

Nevertheless, the criteria defined in [31] do not take into account the special behavior of the TBR algorithm. As the number of destination nodes and paths increases, the great number of probes needed to find different paths, especially if they require strict specifications of QoS, becomes a risk for the scalability of the protocol. This is because of the large number of routing packets that has to be transmitted in the whole network. Obviously, routing protocols must be able to send at least a very small amount of control traffic, in order to discover a topology. Nevertheless, this bootstrapping discovery traffic should be small, since most of the energy is consumed by both transmissions and receptions. This is why

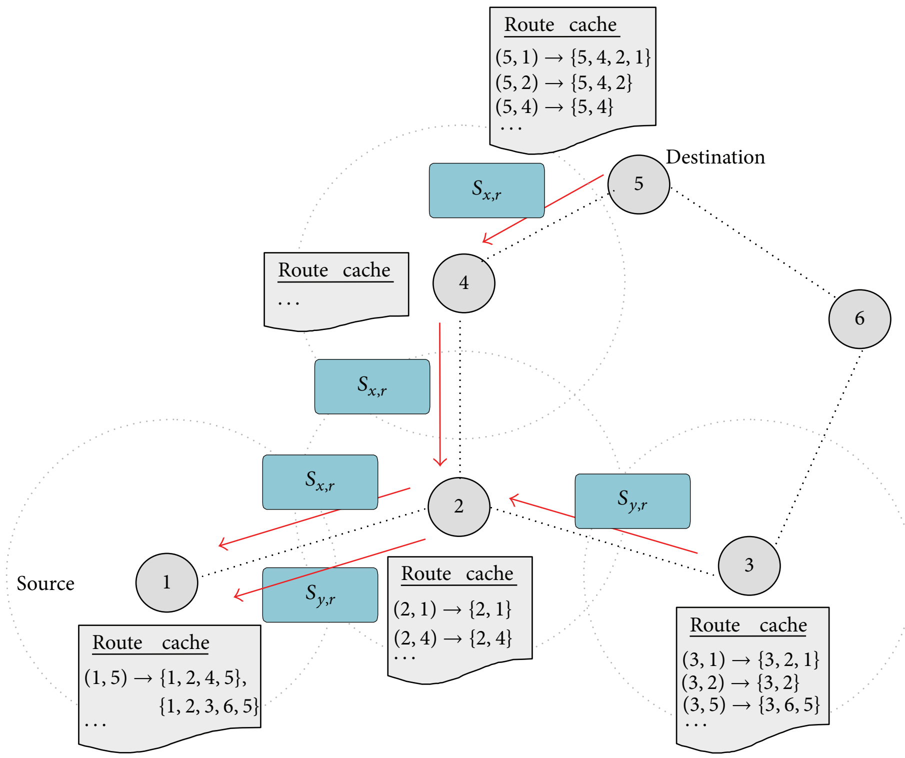

Figure 2: New search of a path (probes receiving).

evolutionary computation techniques are applied in GATAS to improve this TBR protocol aspect, although within the established limits in [31], it turns into the weakest point.

3.2. Underlying Genetic Algorithm Description. GATAS is a randomized forwarding TBR scheme that has been improved using a GA. The resulting QoS-aware routing protocol is decentralized and on-demand based. By using the GA, GATAS reduces latency and routing overhead due to the high number of tickets sent by baseline TBR for finding a valid route to the destination. It uses the parallelized multifocus population-based search provided by GA to search new solutions without any extra consumption of bandwidth. Each source node uses the GA, in an online manner, during the TBR's search phase for new routes, which meets the constraints of the communication to the destination. The main goal of this paper is that it bridges the gap between GA and QoS-aware routing protocol for a Smart Grid. The following section discusses the proposed solution.

3.2.1. Chromosome Codification. The first key element is to choose a proper codification of the chromosome, since it will determine the search space and the mobility through this search space. Several chromosome codification strategies have been successfully used in data network routing algorithms and topology control in ad hoc mesh networks. The network representation could be used in order to code the chromosome of the GA.

Two main strategies have been used to code a chromosome in ad hoc networks. For example, [26] proposed to codify the complete tree of the network in the chromosomes because the sensor network is expressed by a tree network and the genes are expressed by the tree junctions. The main problem of this proposal is that a topology extraction mechanism is needed for that method, which minimizes the value of GA unless it is used in an offline manner inside large networks. In [34], a chromosome of the GA consists of sequences of positive integers that represent the IDs of nodes through which a route path passes. This second flavor has been chosen for on-demand GATAS routing protocol as this fits perfectly with the underlying QoS routing protocol. Internet protocol (IPv6) addresses could be used as the node ID.

Therefore, as shown in Figure 3, each GATAS chromosome is an existing path between the source node and the destination node. There are as many genes as intermediate nodes in the complete path. Thus, the size of the chromosome depends on the number of intermediate nodes. Chromosome genes are coded by the host-addressing part of the IPv6 address. A chromosome provides a possible routing solution, and the population is formed by individuals representing all the evaluated paths.

3.2.2. Fitness Formulation. GAs guide the search toward fitter solutions; therefore, the definition of a fitness function that identifies which are the goal solutions is the second key for success. The fitness function of GAs is generally the objective function that requires to be optimized. QoS-aware routing algorithms attempt to find an optimized path based on one or more QoS metrics. GATAS protocol can work whichever

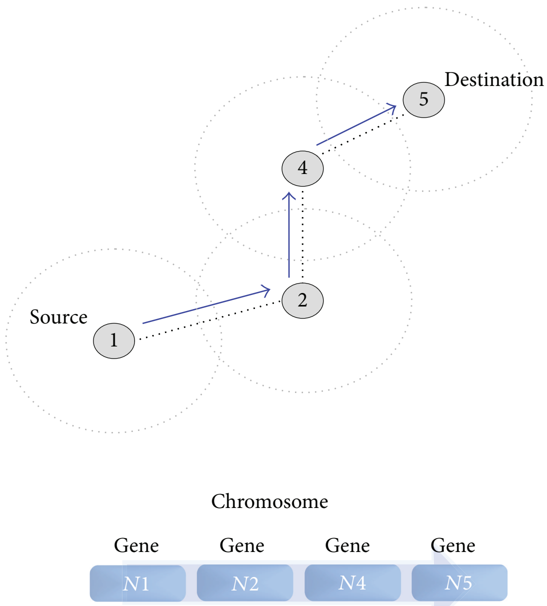

Figure 3: Chromosome coding.

metric strategy is used as GATAS copes with the drawback of multiobjective NP-complete problem [35]. The reason is that the cost of the path is computed in real time during the probe's trip from source node to destination due to its on-demand nature. GATAS routing capabilities are not limited by using a relax path criteria or by using concave metrics [22, 35]. While a feasible path can be selected using any shortest path algorithm [24], additional optimality constraint needs to be imposed to achieve a feasible QoS-aware path [12]. QoS metrics choice is a critical decision as the challenge for sensor ad hoc networks is to design a routing protocol that can adapt to the wide variety of conditions that may appear in Smart Grid networks over time. Metrics should be orthogonal to each other so that there is no redundant information among the metrics.

The results presented in this paper are based on a multipath dynamic delay metric (Table 3), the most important metric for several Smart Grid functions [5, 12, 13, 19], although any QoS metric strategy could be applied by using the proposed routing algebra (Table 4).

3.2.3. End Condition. The end condition is responsible for deciding when to stop the search for a better solution. Typically, in the real world, the application of the GA is run either for a fixed number of iterations or till the search has not been able to find better solutions for a number of iterations. In the parameterization of GATAS algorithm, several end conditions have been used. Actually, QoS-aware routing problem, given a source node s, a destination node d, a set of constraints C and an optimization goal, pursues finding the best feasible successor (2) or several conforming paths from s to d, which satisfies C (3), if multipath routing is desired. Since a QoS-aware routing protocol must search for routes with sufficient resources in order to satisfy the QoS

Table 3: Routing policy based on delay metric.

Element	Description
Σ	$\sigma \in R^{+}$ (real positive numbers)
$\bigoplus$	$\lambda_{ik} \bigoplus \sigma_{kj} = \lambda_{ik} + \sigma_{kj} \mid k \in N_i$
L	$\lambda \in R^{+}, \lambda = \text{delay}$
$\preccurlyeq$	$\leq$

requirements of a flow, this is fairly a suitable end condition for real operation. This end condition must not increase unnecessarily the latency of the network. Although in order to carry out the parameterization of the GA attributes, other end conditions have been used such as certain number of GA iterations, however, they can hardly be used in a real scenario. In our simulation scenarios, the end condition could be configured during simulation time.

Consider the following:

$$S_{ij} = \left\{k \mid \widehat{\sigma}^{i}_{ikj} = \min \sigma_{ij}, \forall k \in N_i\right\}, \tag{2}$$

$$S_{ij} = \left\{k \mid \widehat{\sigma}^{i}_{ikj} \left\langle \left(\min \sigma_{ij} \cdot \gamma\right), \forall k \in N_i\right\} \mid \gamma \right\rangle 1. \tag{3}$$

3.2.4. Initial Population. The initial population should be supplied with sufficient variety of genetic material so that the genetic pressure could lead the population toward better individuals. Therefore, the existence of partial solutions is necessary for the success of the genetic search. The correctness of the path coded by the chromosome inside the actual network topology is critical, so it must be carefully verified by our methodology in order to avoid potential gibberish. However, if the initial population is randomly created as usually done in GA application, it is always necessary to check whether individuals are valid, and they can exist when a new generation is created or when a genetic operation is applied.

To avoid this problem, instead of a random generation, GATAS relies on the underlying QoS routing protocol to obtain suitable paths for the initial population and to avoid a mismatch between actual topology and new individuals. Thus, the existence of each individual of the initial population does not need to be verified by a topology extraction mechanism. The maximum number of initial individuals is limited by the number of available tickets issued by the origin of the path request process. In this way, the genetic algorithm cycle is activated by a source node, only when the search phase of the underlying QoS routing protocol is needed. It is important that GATAS uses the GA in an online manner like in real-time systems [12, 28]. The reason is that the path repair function could be activated by the neighbor discovery process and it is crucial that the repair function is not activated during the search phase as the routing protocol will converge slowly.

3.2.5. New Mutation Operator. The mutation operator is responsible for locally searching new solutions in the parent's neighborhood. In our case, mutation is applied gene by gene. Legacy mutation operator allows modifying any of the genes of a chromosome from the mutation probability. The mutation, as it has been defined in GATAS, requires the node

Table 4: Routing policy based on several additive metrics.

Element	Description
Σ	$\Sigma_{\text{delay}} \times \Sigma_{\text{hop}} \times \Sigma_{\text{bandwidth}_{\text{inversion}}} : \langle \sigma_d, \sigma_h, \sigma_{bi} \rangle$
$\bigoplus$	$(\lambda_d, \lambda_{bi}) \bigoplus (\sigma_d, \sigma_h, \sigma_{bi}) = \langle \lambda_d + \sigma_d, \sigma_h + 1, \lambda_{bi} + \sigma_{bi} \rangle$
L	$\lambda_d \in R^+, \lambda_d = \text{delay}$ $\lambda_{bi} \in R^+, \lambda_{bi} = \dfrac{1}{\text{bandwidth}}$
$\preccurlyeq$	$(\sigma_d, \sigma_h, \sigma_{bi}) \preccurlyeq (\sigma'_d, \sigma'_h, \sigma'_{bi})$ if and only if $(\sigma_d < \sigma'_d) \vee (\sigma_d = \sigma'_d \wedge \sigma_h < \sigma'_h) \vee (\sigma_d = \sigma'_d \wedge \sigma_h = \sigma'_h \wedge \sigma_{bi} \leq \sigma'_{bi})$

to send a new one-ticket probe to obtain a mutated path. The generation of infeasible chromosomes, which violate the current network topology, is avoided by using the underlying QoS routing protocol.

In the process of Figure 4, the gene $N2$ of an individual, like path no. 10, has been selected for mutation. Therefore, the source node sends an m type one-ticket probe (mutation type probe $S_{1,m}$) to the mutation point, in this example the node $N2$. Then, node $N2$ uses the underlying QoS-aware routing protocol to search for another path by issuing a p type one-ticket probe (request type probe $S_{1,p}$) to the destination node $N5$. When the packet $S_{1,p}$ arrives at the required destination node, an r type one-ticket probe (response type probe $S_{1,r}$) is transmitted to the origin in order to advertise a new potential route to the destination $N5$. In that example, you can observe how a hypothetical individual such as $\{N1, N2, N4, N5\}$ mutates into the individual $\{N1, N2, N3, N6, N5\}$. GATAS generates one and only one new individual obtained from a successful mutation phase of each individual. This fact limits the number of extra routing packets overhead to one packet per chromosome mutation.

3.2.6. Crossover Operator. The crossover operator is responsible for the identification and reassembly of subsolutions with the aim of creating better solutions. In our specific problem, the crossover operator is used to expand the search space by finding paths unknown to origin during the search phase of the on-demand routing protocol. The flexibility provided by GATAS enables the application of different crossover schemes. In the experiments conducted herein, we applied 1-point crossover since we tried to avoid an overdisruptive approach in the reproduction phase. Nevertheless, we acknowledge that a more detailed study on which crossover operator would be the best is an interesting future line of research.

The crossover operator works as follows: to start with, the individuals for the crossover must be chosen, selected from the current population from the crossover probability. In addition to this, the crossover point between both individuals must also be chosen. The crossover process does not need any extra routing packet because it is locally executed in the source node during the search path phase of GATAS.

4. Genetic Algorithm Parameterization

In this section, we analyze in detail several results obtained throughout the OPNET simulations of GATAS in order to carry out the required parameterization of the underlying GA and the TBR for its use in the Smart Grid sensor networks.

4.1. Models for the Parameterization of the GA. In order to study the behavior of GATAS protocol in a Smart Grid scenario, we used the OPNET Modeler, which is a network simulation tool oriented to events. All the nodes of the network obey the state machine of Figure 5. The most important states of the finite state machine (FSM) are shown in Table 5.

The studies carried out in this paper are focused on the parameterization of the underlying QoS routing protocol and the underlying GA of GATAS. Furthermore, our study focuses on the analysis of the improvement using a GA compared with the underlying QoS routing protocol. The GA parameterization and the analysis carried out are specifically for ticketing issues, QoS metric, initial population, crossover probability, mutation probability, end condition, selection method, bandwidth requirements, routing overhead, and response time.

Simulated scenarios are based on networks that have more than 100 sensor nodes with reduced mobility. This behavior is likely to occur in the future Smart Grids based on heterogeneous Power Line Communications (PLC) plus wireless networks [7, 17]. For example, AMR systems can intelligently integrate the actions of all users connected to it in order to efficiently deliver sustainable electricity supplies using narrowband PLC and Zigbee communications [5, 12, 19]. The Smart Grid network topology may change due to channel characteristics. Disconnections and lowest bit rates may arise when there is significant interference from outside sources or other transmitting nodes. During these periods of time, network topology may change rapidly [17].

4.2. GATAS GA Parameterization. In this point, the decision of the most important parameters of the GA will be justified. Through Figure 6, the initial population of the GA and how many generations will be necessary for its correct operation (a possible end condition) could be determined. These simulations have been carried out by means of the Roulette Wheel Selection method with a crossover probability of 95% and a mutation probability of a 1%. These probabilities will be justified later and the evaluation of the selection method choice is out of the scope of this paper. Elitism is applied by copying the best individual to the next generation in every GA iteration.

In Figure 6, it is observed that up to an initial generation of 100 tickets, the system continues improving. From that value on, almost the same final result is obtained every time, and no additional improvement is obtained by issuing more initial tickets. The only exception that improves over 100 tickets is the TBR with 0 iterations because, since the number of tickets increases, there are more available routes. Thus, an initial population of 100 individuals could be a suitable one with acceptable bandwidth consumption. Figure 6 could also help us to choose the number of generations that our system

Table 5: Finite state machine of the GA.

State	Description
INIT	The FSM of a GATAS node begins in this state, where all the variables needed for the rest of the process are initialized. In this first state, the routing algorithm and the neighbor discovery algorithm are activated.
Wait	The process remains in the wait state waiting for any interruption to jump to one or another state depending on the interruption arrived at.
Hello	This state manages the neighbor discovery process. It operates in the link layer, and it is responsible for the discovery of other nodes directly connected to the origin, thereby determining the node address and its associated link metric (L). This process implements a basic keep-alive mechanism controlled by the routing protocol.
Routing	This is the state that manages the underlying QoS routing protocol as it has been succinctly described in Section 3.
GA, mutation, and solve	These states are all related with the underlying genetic algorithm as described in Section 3.

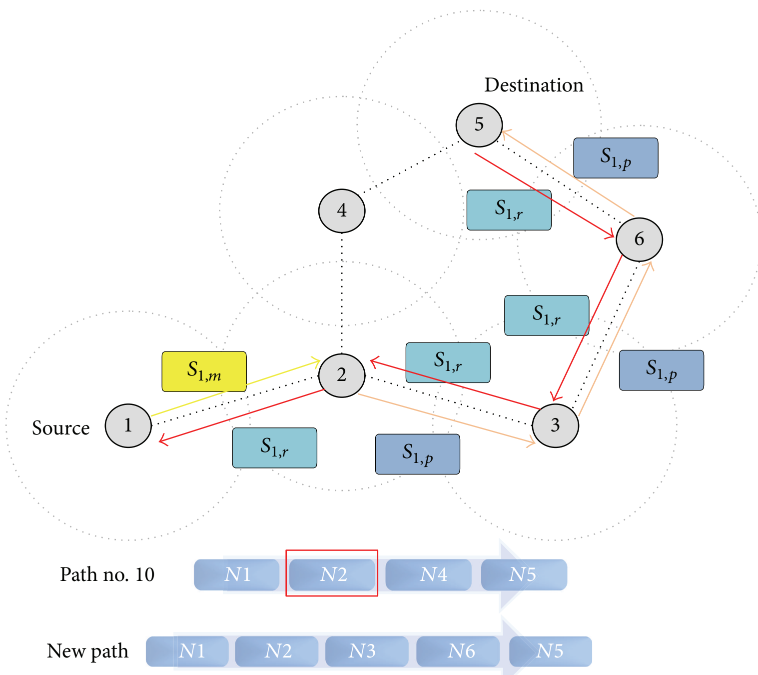

Figure 4: Mutation example (where $N2$ is the mutation point).

has to produce at most, and, therefore, it will set a candidate for an end condition based on the maximum number of iterations. Note that in most of the cases, it is nonsense to evolve the system more than 10 generations, because it does not practically improve the best obtained path. We must take into account that the optimal end condition for a routing algorithm is to obtain the desirable number of feasible paths that satisfy all the QoS constraints by allowing a premature convergence.

Figures 7 and 8 illustrate the crossover and mutation probabilities, and they clearly show that the best performance of the system is at a crossover probability of 95%. At a crossover probability of 10%, the system does not evolve as the final solution (the shortest path) is almost the same as the basic TBR gets. From the outset, there are three possible candidates as the best mutation probability: 1%, 10% and 20%. The mutation probability has a drastic effect on the usage of the network bandwidth. As stated before, a mutation requires to send a new probe packet; this means that, if we increase the mutation probability by too much, the network could be collapsed by routing overhead. Note that with a probability of 20%, 20 new probes are sent for each GA iteration, for each destination by every origin node. This explains our decision to choose a mutation probability of a 1%.

The recapitulation of the achieved GA parameterization after the carried out simulations and experiments can be seen in Table 6.

4.3. Simulation Conclusions. Overall, the effectiveness of our GATAS routing algorithm scheme has been tested through a series of 50 simulation experiments. The bandwidth usage of our algorithm was determined by reckoning the number of packets that each node has generated in simulations. As expected, the network usage increases as the number of initial tickets is increased. The most outstanding peaks are in those nodes with many ad hoc interconnections, a fact that makes

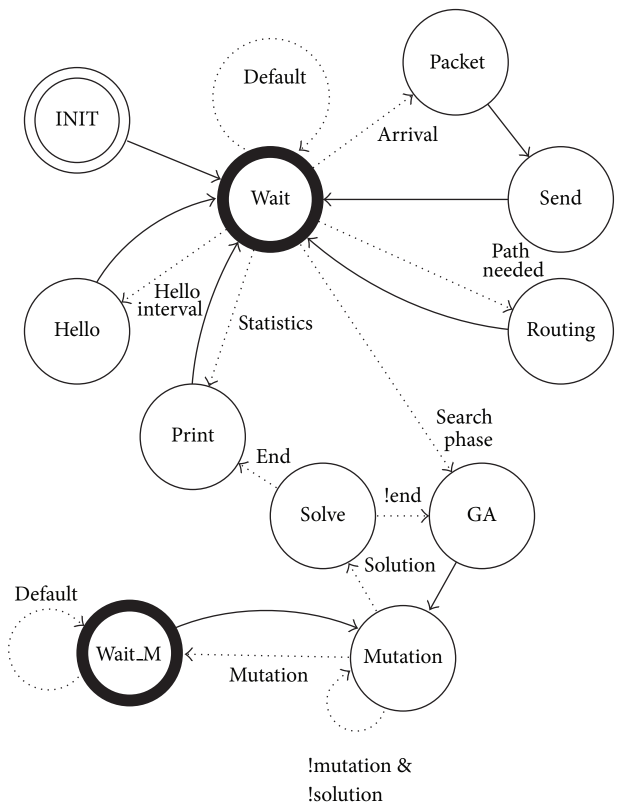

FIGURE 5: Finite state machine of the GATAS router OPNET processor.

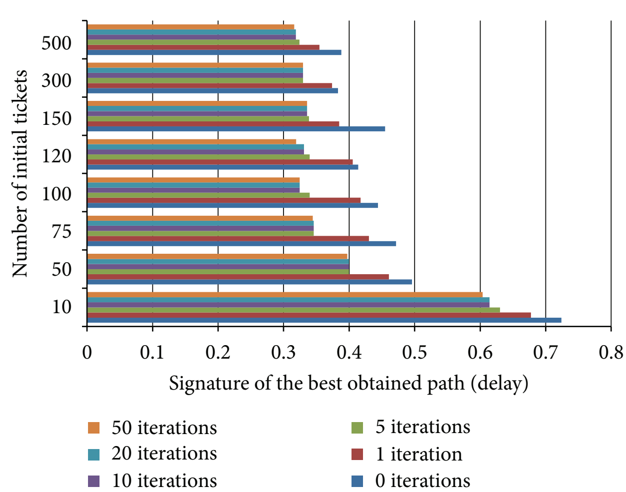

FIGURE 6: Genetic algorithm study for parameterization.

them have to deal with more tickets. At this point, three different case studies have been analyzed in order to assess the improvements introduced by the GA-based approach in the underlying QoS ad hoc routing protocol: TBR with 100 tickets, TBR with 1000 tickets, and GATAS algorithm with the final parameterization. The given convergence time results are standardized at 1 time unit.

In the TBR scenario with 100 tickets, the shortest path that the TBR has achieved in the best simulated case study is

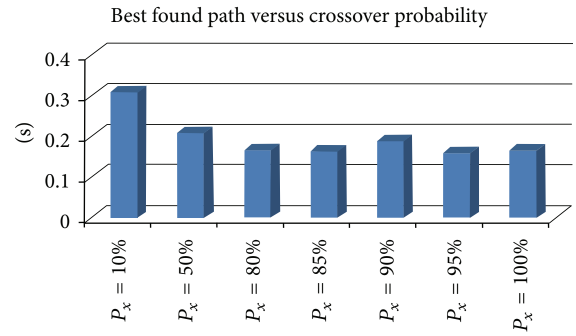

FIGURE 7: Crossover probability studies (average).

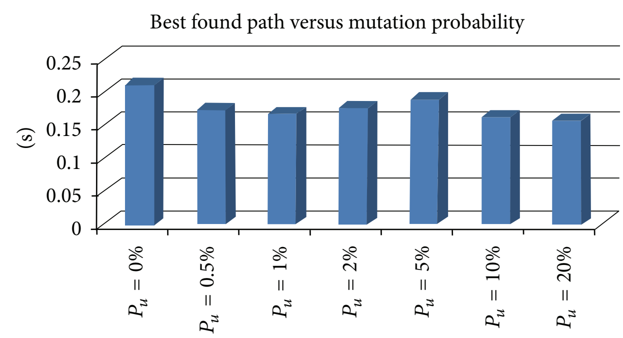

FIGURE 8: Mutation probability studies (average).

TABLE 6: GATAS genetic algorithm parameterization for smart grids.

Parameter	Value
TBR method	Random TBR
Initial population	100 individuals
Selection method	Roulette Wheel Selection
Elitism	Yes
End condition 1	Feasible QoS path found
End condition 2	10 GA iterations
Crossover probability	0.95
Mutation probability	0.01

obtained in a response time of 75 time units with a path cost of 0.248 seconds. On average, TBR with 100 tickets takes 94 time units to give us the best route it can get during the whole simulation time, and it has a path cost of 0.459 seconds. It is important to keep in mind that TBR with 100 tickets takes an average of 280 time units to send us all probes with valid paths with a maximum convergence time of 299 time units. Table 7 shows the results of the three case study scenarios. In it, the best path (metric delay in seconds) and the simulation real time needed to obtain the resulting feasible paths by using an orthogonal unit to the deployed network (OPNET simulation units [u]) can be noticed.

In the TBR scenario with 1000 tickets, we will find more and better routes than TBR with 100 tickets since there are more tickets. In contrast, the convergence time of the

Table 7: Results comparison.

	Best shortest path—simulation time	Average best feasible path—simulation time	Convergence time
TBR (100 tickets)	0.248 seconds—75 [u]	0.459 seconds—94 [u]	280 [u]
TBR (1000 tickets)	0.177 seconds—162 [u]	0.381 seconds—486 [u]	1762 [u]
GATAS	0.169 seconds—283 [u]	0.344 seconds—394 [u]	626 [u]

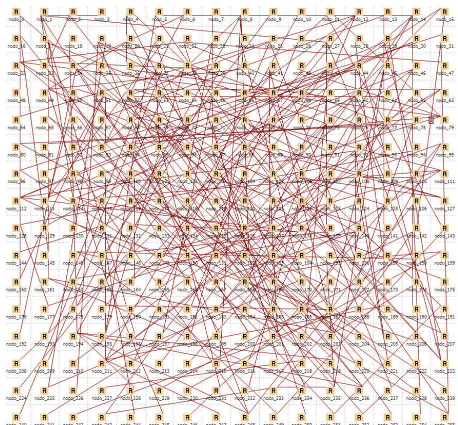

Figure 9: Example of an automatic generated scenario.

routing protocol is more than 6 times higher, and the routing overhead is more than 9 times higher.

GATAS response time is directly affected by the response time of TBR, since the GA is not activated until the TBR has completely generated the initial population of 100 individuals and these are either received or their timeout has expired. The mutation operation is the only one that adds delay to the convergence time since it is the only one that generates an extra probe routing packet which must be waited for in order to be processed. However, GATAS provides the best balanced ratio of best found feasible path to response time in the simulations carried out. Regardless of the convergence time of the TBR with 100 tickets, the GATAS results are the best by far in all the automatic generated scenarios by OPNET (e.g., Figure 9).

4.4. Future Comparisons. In future work, other ad hoc routing protocols must be compared with GATAS over a standard Medium Access Control (MAC) wireless level in order to evaluate its commercial utilization. To this respect, our main goal for further work is to develop the GATAS protocol in a general purpose development platform module for IEEE 802.15.4/6lowpan compatible Wireless Sensor Networks. The future objective is to assess the protocol designed to empirically monitor the consumption parameters and their convergence times. The comparison has to be made between the parameterized GATAS protocol and real mature protocol implementations which provide a feasible contrast in the created working environment.

The only algorithm that, so far, could be compared with the GATAS algorithm is the IPv6 Routing Protocol for Low Power and Lossy Networks (RPL) [36] as the IETF ROLL Working Group focuses specifically on the IPv6 routing architectural, which has been recently specified by the IETF. For this reason, the comparison will be done when the first devices are launched in 2013-2014 and when we conclude our development. RPL intends to support a variety of low-cost network applications including industrial monitoring, building automation, connected homes, health care, environmental monitoring, urban sensor networks (e.g., Smart Grid), and asset tracking.

5. Conclusions and Further Work

GATAS routing protocol based on QoS-aware ad hoc routing has been presented as the evolution of its predecessor, the TBR algorithm. The study has concluded that this enhanced protocol based on evolutionary computation techniques improves many aspects in an M2M communication network such as optimal found path and convergence time. The main advantage is the increment of the network efficiency by minimizing routing overhead and by increasing the practicable bandwidth with the same resources.

Given that on-demand routing protocols for multihop ad hoc networks can result in increased packet latency, the paper has successfully applied GA to the existing TBR routing protocol to create the GATAS routing protocol that improves the mentioned latency aspect over that in TBR to better fit the Smart Grid requirements.

The design of an ad hoc QoS-aware routing protocol is more demanding than a shortest path routing protocol. The reason is the increase in the number and exigency of usable paths. On the other hand, the amount of routing information to transmit is greater. As our experiments demonstrate, GATAS is a better protocol to use for Smart Grids than TBR scheme. Overall, this paper presents the results of an incipient research work. In terms of CPU runtime and complexity, GATAS is comparable with TBR and other similar routing protocols with the difference that GATAS could be aware of multiple QoS metrics, the thing that is fit to the Smart Grid nature and requirements. In terms of energy saving, convergence time, overhead, and effectiveness, GATAS greatly improves its predecessor. Several trends were clearly visible in this study but the most important is that evolutionary techniques have been successfully applied to a QoS-aware ad hoc routing protocol for Smart Grids networks.

Conflict of Interests

The authors certify that there is no conflict of interests with any financial organizations regarding the material discussed in the paper.

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References

[1] V. C. Gungor, D. Sahin, T. Kocak et al., "A survey on smart grid potential applications and communication requirements," *IEEE Transactions on Industrial Informatics*, vol. 9, no. 1, pp. 28–42, 2013.

[2] EPRI's IntelliGrid initiative, Electric Power Research Institute, 2011, http://intelligrid.epri.com/.

[3] U.S. Department of Energy, "Communication requirements of smart grid technologies," 2010.

[4] A. Vallejo, A. Zaballos, J. M. Selga, and J. Dalmau, "Next-generation QoS control architectures for distribution smart grid communication networks," *IEEE Communications Magazine*, vol. 50, no. 5, pp. 128–134, 2012.

[5] Y. Yan, Y. Qian, H. Sharif, and D. Tipper, "A survey on smart grid communication infrastructures: motivations, requirements and challenges," *IEEE Communications Surveys and Tutorials*, vol. 15, no. 1, pp. 5–20, 2012.

[6] Q. Yang, J. A. Barria, and T. C. Green, "Communication infrastructures for distributed control of power distribution networks," *IEEE Transactions on Industrial Informatics*, vol. 7, no. 2, pp. 316–327, 2011.

[7] A. Zaballos, A. Vallejo, and J. M. Selga, "Heterogeneous communication architecture for the smart grid," *IEEE Network*, vol. 25, no. 5, pp. 30–37, 2011.

[8] D. E. Goldberg, *Genetic Algorithms in Search, Optimization & Machine Learning*, Addison-Wesley, Reading, Mass, USA, 1989.

[9] J. H. Holland, *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control and Artificial Intelligence*, MIT Press/Bradford Books edition, 1992.

[10] OPNET University Program, 2011, http://www.opnet.com/services/university/.

[11] INTEGRIS FP7 Project 'INTelligent Electrical Grid Sensor communications' ICT-Energy-2009 call (number 247938), http://fp7integris.eu/.

[12] J. Navarro, A. Zaballos, A. Sancho-Asensio, G. Ravera, and J. E. Armendariz-Iñigo, "The information system of INTEGRIS: INTelligent Electrical GRId sensor communications," *IEEE Transactions on Industrial Informatics*, no. 99, p. 1, 2012.

[13] H. Li and W. Zhang, "QoS routing in smart grid," in *Proceedings of the 53rd IEEE Global Communications Conference (GLOBECOM '10)*, pp. 1–6, December 2010.

[14] Y.-J. Kim, M. Thottan, V. Kolesnikov, and W. Lee, "A secure decentralized data-centric information infrastructure for smart grid," *IEEE Communications Magazine*, vol. 48, no. 11, pp. 58–65, 2010.

[15] E. Bou-Harb, C. Fachkha, M. Pourzandi, M. Debbabi, and C. Assi, "Communication security for Smart Grid distribution networks," *IEEE Communications Magazine*, vol. 51, no. 1, pp. 42–49, 2013.

[16] P.-Y. Chen, S.-M. Cheng, and K.-C. Chen, "Smart attacks in smart grid communication networks," *IEEE Communications Magazine*, vol. 50, no. 8, pp. 24–29, 2012.

[17] H. Gharavi and B. Hu, "Multigate communication network for smart grid," *Proceedings of the IEEE*, vol. 99, no. 6, pp. 1028–1045, 2011.

[18] A. Zaballos, A. Vallejo, G. Ravera, and J. M. Selga, "Simulation and analysis of a QoS multipath routing protocol for smart electricity networks," *International Journal on Advances in Networks and Services*, vol. 3, no. 3-4, pp. 417–429, 2011.

[19] B. Sivaneasan, P. L. So, and E. Gunawan, "A new routing protocol for PLC-based AMR systems," *IEEE Transactions on Power Delivery*, vol. 26, no. 4, pp. 2613–2620, 2011.

[20] M. Ilyas, *The Handbook of Ad Hoc Wireless Networks*, CRC Press, Boca Raton, Fla, USA, 1st edition, 2003.

[21] M. L. P. Bueno and G. M. B. Oliveira, "Multicast flow routing: evaluation of heuristics and multiobjective evolutionary algorithms," in *IEEE Congress on Evolutionary Computation (CEC '10)*, July 2010.

[22] A. Riedl and D. A. Schupke, "Routing optimization in IP networks utilizing additive and concave link metrics," *IEEE/ACM Transactions on Networking*, vol. 15, no. 5, pp. 1136–1148, 2007.

[23] A. Singh and S. Sundar, "An artificial bee colony algorithm for the minimum routing cost spanning tree problem," *Soft Computing*, vol. 15, no. 12, pp. 2489–2499, 2011.

[24] W. A. Chang and R. S. Ramakrishna, "A genetic algorithm for shortest path routing problem and the sizing of populations," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 6, pp. 566–579, 2002.

[25] F.-N. Pavlidou and G. Koltsidas, "Game theory for routing modeling in communication networks—a survey," *Journal of Communications and Networks*, vol. 10, no. 3, pp. 268–286, 2008.

[26] L. Barolli, A. Koyama, and N. Shiratori, "A QoS routing method for ad-hoc networks based on genetic algorithm," in *International Workshop on Database and Expert Systems Applications*, 2003.

[27] D. Apiletti, E. Baralis, and T. Cerquitelli, "Energy-saving models for wireless sensor networks," *Knowledge and Information Systems*, vol. 28, no. 3, pp. 615–644, 2011.

[28] A. C. B. Garcia, C. Bentes, R. H. C. de Melo, B. Zadrozny, and T. J. P. Penna, "Sensor data analysis for equipment monitoring," *Knowledge and Information Systems*, vol. 28, no. 2, pp. 333–364, 2011.

[29] N. Guofang and L. Minqiang, "Evolutionary based approaches in wireless sensor networks: a survey," in *Proceedings of the 4th International Conference on Natural Computation (ICNC '08)*, pp. 217–222, October 2008.

[30] V. Uchhula and B. Bhatt, "Comparison of different Ant Colony Based Routing Algorithms," *International Journal of Computer Applications*, no. 2, pp. 97–101, 2010.

[31] P. Levis, A. Tavakoli, and S. Dawson-Haggerty, "Overview of Existing Routing Protocols for Low Power and Lossy Networks," IETF Draft-Letf-Roll-Protocols-Survey-07, pp. 1–27, 2009.

[32] J. L. Sobrinho, "An algebraic theory of dynamic network routing," *IEEE/ACM Transactions on Networking*, vol. 13, no. 5, pp. 1160–1173, 2005.

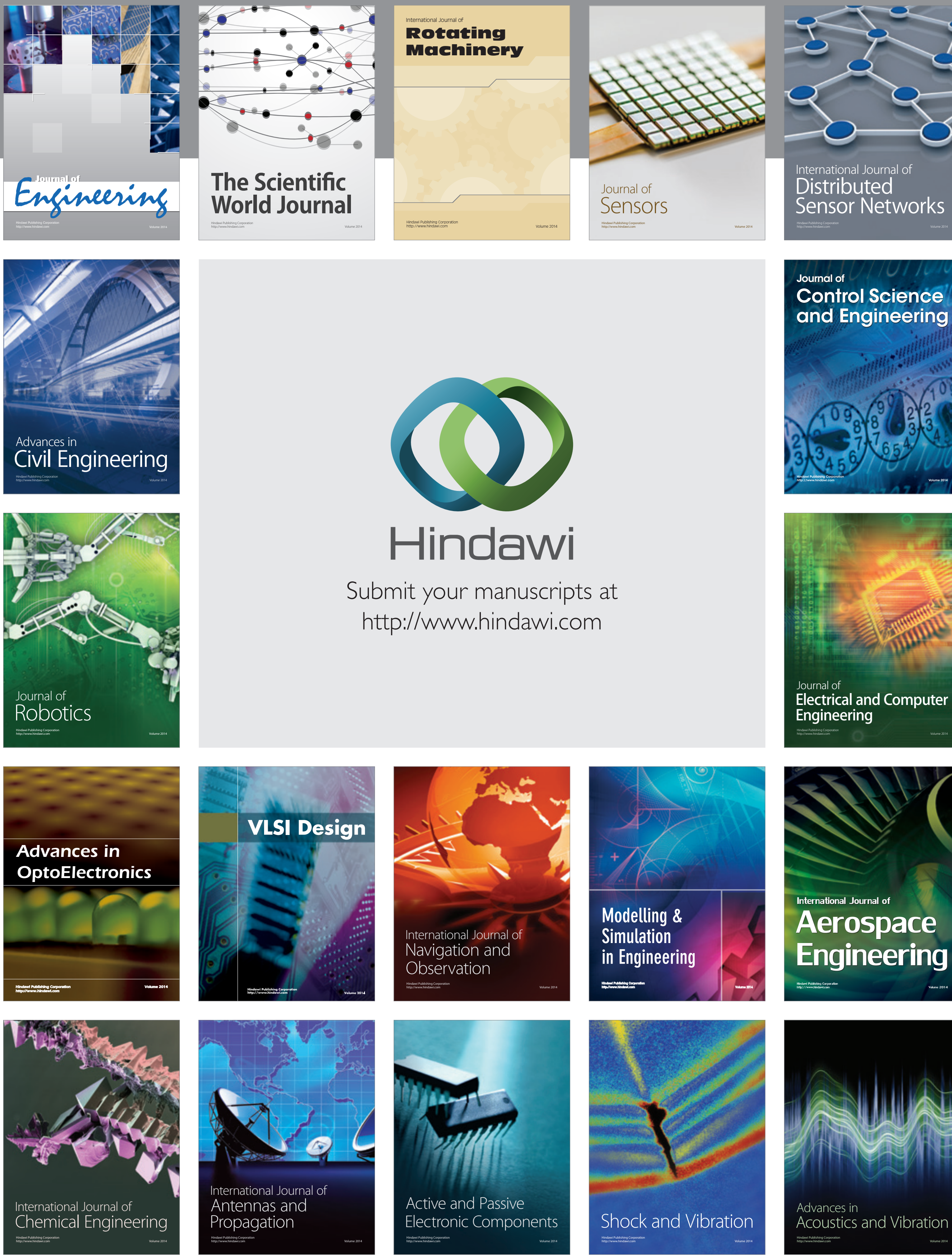
[33] X. Li, W. Jun, and K. Nahrstedt, "The enhanced ticket-based routing algorithm," in *Proceedings of the International Conference on Communications (ICC '02)*, pp. 2222–2226, May 2002.

[34] P. Sateesh and S. Ramachandram, "Scalability of network size on genetic zone routing protocol for MANETs," in *Proceedings*

of the International Conference on Advanced Computer Theory and Engineering (ICACTE '08), pp. 763–767, December 2008.

[35] Z. Wang and J. Crowcroft, "Quality-of-service routing for supporting multimedia applications," *IEEE Journal on Selected Areas in Communications*, vol. 14, no. 7, pp. 1228–1234, 1996.

[36] P. Thubert, T. Winter, A. Brandt et al., "RPL: IPv6 Routing Protocol for Low power and Lossy Networks," *IETF Draft-Letf-Roll-Rpl-18*, pp. 1–160, 2011.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