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SESSION 1: METROLOGY AND QUALITY CONTROL IN THE PRODUCTION ENGINEERING

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Nedeljković, D., Petrović, M., Jakovljević, Ž.

COMPARISON OF PARTICLE SWARM AND ANT COLONY OPTIMIZATION IN WIRELESS SENSOR NETWORK ROUTING

Abstract: *Wireless Sensor Networks (WSNs) represent an indispensable means for data acquisition from distributed devices within Industry 4.0. WSN consists of sensor nodes placed randomly in a plant. As a rule, their allocation does not provide the possibility for direct transmission of data between two nodes, and multi-hop data transfer is necessary. WSN energy efficiency is an important issue and to address it the communication effort should be minimized. One of the most effective ways to achieve this is routing, i.e. the process of finding the optimal path from the transmitting to the receiving node. In this paper, we compare four different routing algorithms, based on particle swarm and ant colony optimization.*

Key words: *Wireless Sensor Network, routing, Particle Swarm Optimization, Ant Colony Optimization*

1. INTRODUCTION

To answer the fluctuating needs of globalized market, Industry 4.0 manufacturing enterprises have to embrace reconfigurable manufacturing systems (RMS) [1]. These systems are highly based on ubiquitous communication of field devices which can be easily reconfigured for manufacturing of high diversity of different products. Usually the communication is based on wireless technologies that enable easy reconfiguration and mobility of manufacturing assets. Thus, wireless networks, and in particular wireless sensor networks (WSN), represent one of the key enabling technologies for Industry 4.0 concept, and they will be applied in a number of different manufacturing control applications. Due to the changeable structure of RMS, corresponding WSN consists of randomly distributed sensor nodes which communicate the data within the system. A key characteristic of sensor node is its communication range, i.e. the largest distance between the node and adjacent nodes in the environment that the node can communicate with. Allocation of two nodes does not always give the possibility for direct data exchange, i.e. the transmitting and receiving nodes are not always within communication range. In such a case, the data are transmitted using multi-hop communication, in which additional nodes are used as intermediaries for message transfer. Additional nodes have to enable the chain for reliable message transfer, that is, the adjacent nodes in the chain have to be within mutual communication distance. In a number of applications the nodes are battery powered, and energy consumption represents an issue that has to be addressed. Energy that is consumed during the communication is related to the distance between nodes and the number of hops. Thus, the reduction of energy consumption and network lifetime maximization implies the minimization of these two parameters. The procedure for generation of optimal communication route is called routing. Since the positions of nodes are changing dynamically as a consequence of system reconfiguration or resources mobility or due to certain nodes failure, it is necessary to dynamically re-route the transfer path. Effective, possibly real-time applicable routing procedures are crucial for application of WSN in RMS.

The advances in biologically inspired optimization algorithms, led to the development of a number of routing methods based on these techniques. In [2] Particle Swarm Optimization (PSO) is employed, whereas, the routing based on Ant Colony Optimization (ACO) is explored in [3]. In both methods, the optimization is carried out assuming that the optimal routing path is always along the vector from transmitting to the receiving node where each subsequent node in the multi-hop route is approaching the recipient. Nevertheless, as will be presented in the sequel, in a number of WSN deployments the optimal path implies a local turning away from recipient in order to get globally optimal path.

Within this paper we will propose routing methods based on PSO and ACO that will allow local distance increase in order to obtain globally lower energy consumption. Furthermore, we will compare novel methods mutually, and with existing PSO and ACO based methods. The reminder of the paper is structured as follows. In Section 2 WSN routing problem is defined, while

Section 3 gives an overview on how this problem can be solved using considered biologically inspired algorithms. Section 4 presents and discusses optimization results obtained using alternative approaches. Finally, in Section 5 we provide conclusions and future work guidelines.

2. PROBLEM SETUP

In this paper, the routing problem represents a problem of finding optimal path between transmitting and receiving node with respect to energy consumption. Generally, there exist two routing approaches that will be illustrated using a simple WSN deployed as presented in Fig. 1. In this figure, the ranges of nodes are given in dotted red line and they encircle potential destinations in the next hop. In the first approach (used in [2] and [3]) the optimal route is searched among the routes in which it is possible to transmit the signal only to the nodes which are positioned towards the transmitting node. For example, from start node in Fig. 1, using this approach, it is possible to transfer message only to node 1. All possible routes in this case are denoted by light red arrows, and the best route in dark red.

The second approach that we propose in this paper, allows local transmitting to the nodes which are backwards relative to receiving node (node 2 in Fig. 1). In this case, we have a combinatorial explosion of possible paths.

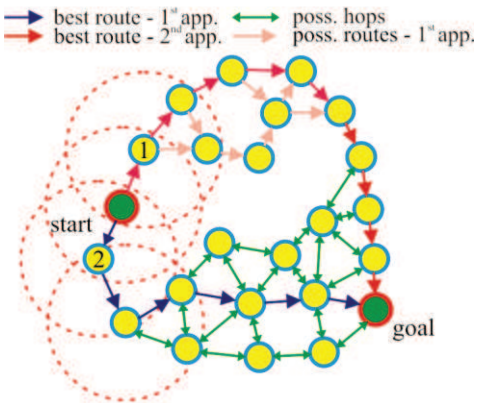

Fig. 1. Considered WSN routing approaches

However, in a number of situations and especially for large networks, second approach leads to globally optimal route, as presented in blue line in Fig. 1. Energy consumption in WSN, which in this case represents optimization objective is related to communication distance and number of hops. When the transmission distance d is lower than threshold value, the energy necessary for transmission of l-bit message is given by [2]:

$$E_T = lE_{elec} + l\varepsilon_f d^2 \quad (1)$$

and for its reception by:

$$E_R = lE_{elec} \quad (2)$$

where E_{elec} is the energy required by electronic circuit and ε_f by amplifier. As can be observed, for given message size, total energy consumption is a function of transmitting distance and number of hops. Thus, to minimize consumed energy, it is necessary to minimize number of hops and total distance. Fitness function that takes into account both parameters can be defined as:

$$F = w_1 d_{tot} + w_2 n \quad (3)$$

where d_{tot} represents the total distance, and n the number of hops along route. Furthermore, w_1 and w_2 (w_1+w_2=1) are weight factors that represent parameter's influence on the fitness function.

3. BRIEF OVERVIEW OF IMPLEMENTED OPTIMIZATION APPROACHES

This section provides a brief overview of the biologically inspired optimization algorithms compared in this paper.

3.1 Particle Swarm Optimization

Particle Swarm Optimization (PSO) algorithm [4] is based on swarm biological principles. PSO model initially contains a number of potential solutions – particles. During algorithm implementation, particles conjointly participate in finding fitness function optimal value in n-dimensional space, where n represents the dimension of particle (number of nodes in WSN). Each particle has assigned position (X_{id}) and velocity (V_{id}), where i denotes particle number, and d is the coordinate in n-dimensional space.

PSO algorithm assigns to each particle its own best fitness function value obtained during iterations denoted as *pbest*. Furthermore, it detects the best global fitness function value for all particles - *gbest*. The values of *pbest* and *gbest* are iteratively detected through particle position and velocity update using the equations:

$$\begin{aligned} V_{id}^{k+1} &= wV_{id}^{k} + c_1 r_1^k (pbest_{id}^k - X_{id}^k) \\ &+ c_2 r_2^k (gbest_d^k - X_{id}^k) \end{aligned} \quad (4)$$

$$X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1} \quad (5)$$

where w represents inertial weight, r_1 and r_2 are uniformly distributed random numbers in range [0,1], while c_1 and c_2 denote acceleration factors. The values of w, c_1 and c_2 are experimentally identified. In PSO based routing [2], the limited number of nodes within the range of each node d are identified and numerically denoted by $l(d)$ = 1,… $N_h(d)$, where $N_h(d)$ is total number of these nodes. The particle position X_{id} has a value in the range [0, 1] for each node d in WSN. There is a correspondence between the value of X_{id} and reachable node $l(d)$, where the range of X_{id} is equally divided between $N_h(d)$ reachable nodes. Namely, if $X_{id}=\in[0, 1/N_h(d)]$ than the next node is node denoted $l(d)=1$, if $X_{id}=\in(1/N_h(d), 2/N_h(d)]$ the next node is $l(d)=2$, etc. In this way X_{id} implicitly defines communication route through chain of nodes $l(d)$ that starts from transmitting and ends at receiving node. In approach from [4] reachable nodes $l(d)$ are only the nodes directed towards receiving node, while in our approach these are all nodes within the range of node d.

3.2 Ant Colony Optimization

Ant Colony Optimization [5] is biologically inspired algorithm in which the behaviour of ants is mapped into virtual model through description of the way in which they mark the path by pheromone trail. When along the path ants have to choose one of the alternative directions, the decision is made based on the pheromone intensity. The probability that k^{th} ant will go from i^{th} to j^{th} point on the road is defined as follows[1]:

$$p_{ij}^{k} = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{l \in N(i)} [\tau_{il}(t)]^{\alpha} \cdot [\eta_{il}]^{\beta}} \tag{6}$$

where τ_{ij} denotes pheromone value, $\eta_{ij} = 1/D_{ij}$, where D_{ij} is the distance between points, and $N(i)$ is the set of points adjacent to the current position i (in our case reachable nodes from node i). Furthermore, coefficients α and β are in the range [0, 1] and they adjust the influence of pheromone and path length, respectively. Pheromone changes during algorithm iterations as follows:

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij} \tag{7}$$

where $1-\rho$ ($\rho \in [0, 1]$) models pheromone evaporation and $\Delta\tau_{ij}=Q/D_{ij}$ denotes the amount of pheromone that the most successful ant in an iteration created (Q is pheromone parameter).

In ACO based routing, each node in the network represents a point on the ant's path. From node i, the ant can go to one of reachable nodes $j(i)=1,\ldots N(i)$. Cumulative probabilistic rule (roulette wheel selection) based on random variable z decides which of reachable nodes will be chosen. Using this rule first identified node q for which:

$$z < \sum_{j=1}^{q} P_{ij} \tag{8}$$

holds is chosen as the next node.

In each iteration a predefined number of ants are dispatched from transmitting node with the goal to come to the receiving node. The maximum number of hops is limited to exclude possible generation of infinite cycles as a result of returning to already visited nodes. Ant with the best value of fitness function (3) is selected and its pheromone values are retained according to (7); in the last iteration, this ant defines the optimal path. Probabilistic decision rule (8) insures avoiding the bias towards the path from previous iteration.

4. EXPERIMENTAL RESULTS

Described algorithms were implemented in MATLAB R2015a and the experiments were carried out. Considered approaches are compared against their main parameters, i.e., number of particles (ants), number of iterations and WSN complexity. The values of these parameters are varied up to the 210 particles (ants), 50 iterations and 80 nodes in WSN. After conducting preliminary experiments, the values of weight coefficients in fitness function (3) were set to $w_1=0.2$ and $w_2=0.8$. These values were experimentally identified and they capture the higher influence of hops on energy consumption as presented in (1) and (2). WSN nodes were deployed within a square of 50 basic length units (BLU), while their range was 7.5 BLU.

PSO parameters were set to: $c_1=2$, $c_2=2$, $w=1.4$, $V_{max}=0.5$, $V_{min}=-0.5$, where $[V_{min}, V_{max}]$ represents velocity range at initialization. Furthermore, ACO parameters were set to: $\alpha=1$, $\beta=0.5$, $\rho=0.6$, $\tau_0=0.8$, and $Q=1$, where τ_0 represents initial value of pheromones. We will denote compared algorithms as follows: PSOdef and PSOupd refer to PSO based algorithms using the first and second approach (Section 2) respectively, whereas ACOdef and ACOupd refer to ACO based algorithms using the same notation as for PSO. Fig. 2 presents comparison results based on number of particles (ants) for WSN with 60 nodes after 15 iterations. From this figure it can be observed that ACO algorithms generally reach optimal values for smaller number of ants. Furthermore, ACOupd needs the smallest number of ants for reaching the best fitness function value. On the other hand, PSOdef and PSOupd reach their own optimal values for the similar number of particles.

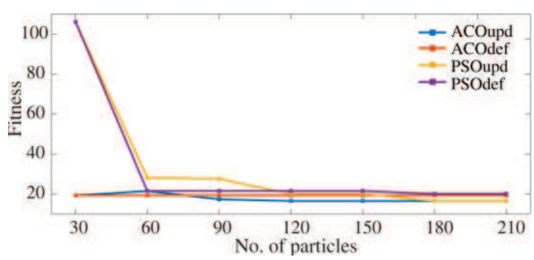

Fig. 2. Best fitness value vs. number of particles (ants) for WSN with 60 nodes after 15 iterations

[1] At the initialisation, the probability that ant will go from point i to any of the adjacent points j is the same.

Algorithms' convergence for 50 iterations with 100 particles (ants) is presented in Fig. 3 (the same WSN with 60 nodes as in Fig. 2 was considered). Here, the significance of the number of selected iterations on algorithm performances can be noticed. Fitness function values in both PSO based algorithms abruptly decrease within the range of only a few iterations. The best results (the smallest value of fitness function) are obtained using ACOupd, followed by the second best PSOupd.

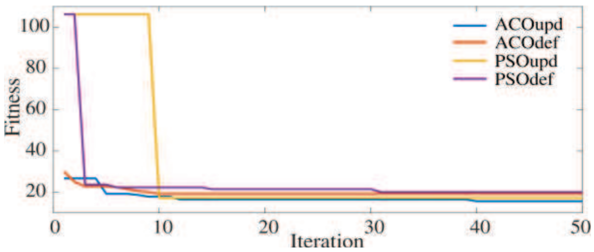

Fig. 3. Algorithm comparison based on number of iterations (WSN with 60 nodes, 50 iterations)

The increase of number of nodes in WSN leads to the increase of the number of possible routes and makes the routing process more complex. The performances of compared algorithms for different WSN sizes are illustrated in Fig. 4; in this comparison the number of ants (particles) was set to 100, and the number of iterations was 100.

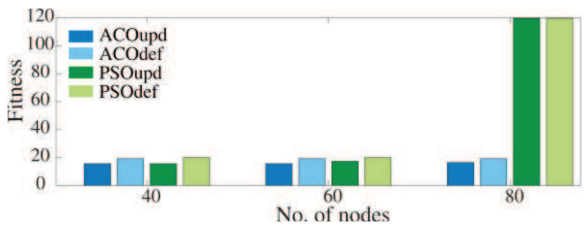

Fig. 4. Algorithms comparison based on the size of WSN (for 100 particles (ants), 100 iterations)

The algorithms were compared for WSNs with 40, 60, and 80 nodes. For all considered WSNs ACOupd performs the best with respect to obtained optimal fitness function value. Furthermore, for smaller number of nodes all algorithms give comparable results. For WSNs with 40 and 60 nodes fitness function value slightly increases. Nevertheless, in the case of WSN with 80 nodes, rapid increase in fitness function value can be observed in the case of PSO algorithms. This indicates that for large WSNs ACO based techniques are techniques of choice.

5. CONCLUSION

In this paper we have compared four biologically inspired WSN routing algorithms. In addition to two existing PSO and ACO based algorithms, we have considered their modified versions - the modifications were proposed in this paper. Comparison was carried out against several criteria, and fitness function value represented the measure of algorithm success. It has been shown that modified versions of algorithms that allow backwards transmission (ACOupd and PSOupd) outperform original algorithms. Based on all criteria, ACOupd presented the best results, whereas it has been shown that the PSO based algorithms have significantly lower performances than ACO based for larger WSNs. The analysis presented in this paper did not considered optimization time, which is another significant parameter for application at hand. This will be the topic of future research. Furthermore, our research efforts will be directed to the application of multi-objective optimization within considered algorithms.

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