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Energy Efficient Software Defined Networking Algorithm for Wireless Sensor Networks

Mohsin Masood[a]*, Mohamed Mostafa Fouad[b], Saleh Seyedzadeh[a], Ivan Glesk[a]

[a]*Electronics and Electrical Engineering Department, University of Strathclyde, G1 1XW Glasgow, UK*
[b]*Arab Academy for Science, Technology and Maritime transport, Cairo, Egypt*

Abstract

The real-time properties and operational constraints of Wireless Sensor Networks (WSNs) have emerged the need for designing energy efficient routing protocols. Recently, software defined network based WSN (SDN-WSN) emerging technology has offered a significant development by untying control logic plane from the low power sensor nodes. This centralized programmable control still suffers from several configuration challenges in distributed sensors environment. Meta-heuristic based SDN approaches had been proposed for the efficient path selection in WSN but they still suffer from both, exploration and exploitation problems. Therefore, this paper addresses these shortcomings by proposing a meta-heuristic based dolphin echolocation algorithm (DEA) for optimizing route selection in WSNs. Objective function of the DEA algorithm is to consider the residual energy of the nodes for selecting energy efficient routes. The proposed algorithm performance is compared with several meta-heuristic algorithms in terms of energy-consumption, and network throughput parameters.

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Keywords: Software defined networks; energy efficient routing; wireless sensor networks; optimization techniques; adaptive dolphin echolocation algorithm;

* Corresponding author. Tel.: +4-755-739-9786.
E-mail address: mohsin.masood@strath.ac.uk

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1. Introduction

Wireless sensor network (WSN) refers to a set of well-organized dispersed sensors networks used for the monitoring and collection of real-time data from its surroundings. These data are aggregated to a predetermined base station. Therefore, routing protocols got significant importance in WSN to meet the new applications Quality of Services (QoS) requirements as described by Choi et al. and Akyildiz et al. Routing protocols differ according to the applications requirements and network architecture. Routing in WSN is always considered as thought-provoking due to its inherent properties that discern these networks from other wireless communication networks such as cellular networks Al-Karaki et al. and Singh et al. In WSN, a large number of sensors are usually deployed and this makes an impossible task to build a global addressing scheme due to the overhead of the ID maintenance. Thus, the traditional IP based protocols may not be applicable for WSN. Sensors used for WSN are tightly constrained in terms of energy, processing and storage capabilities and as such they consequently require cautious management of resources. Furthermore, there is high probability of redundant data to be exploited by routing protocols for the improvement of bandwidth and with it a related energy utilization. To minimize the energy ingesting in WSN, various routing techniques have been proposed that can be classified according to the network architecture. Moreover, these routing protocols can be categorized into multi-path based, quality-of-service (QoS), query-based, and negotiation-based depending on the protocol operation Heinzelman et al. and Silva et al.

Even though WSN is extensively used for diverse applications, yet there are numerous inadequacies in their structural characteristics. For example, due to lacking self-managed method, sensor nodes scheduling cannot be reconfigured. With the advent of software-defined-network (SDN) in combination with WSN major development has been introduced to resource scheduling methods. With the separation of data and control planes, SDN grasps the decoupling of data scheduling function and program management function. SDN helps to buffer the differences in devices and accomplish the reconstruction of hardware resources. Furthermore, with the help of Open Flow protocol extension, SDN controller embedded with WSN makes it possible to build the mapping of virtual physical resources. Routing requirements in WSN are not optimal in terms of “transporting (moving)” the needed information. In addition, related energy consumption also needs to be considered by the network management. To do that various approaches needs to be considered Ndiaye et al., Hu et al. and Lou et al.

2. Related Research Work

Object identification and positioning algorithms gained the significant role in WSN. Due to the failure of the traditional methods of identifying the moving targets, an Interaction Multiple Model based WSN target tracking method was introduced Vasuhi et al. Similarly, considering the energy consumption constraints in WSN, event-based information filtering method was presented Lu et al. For the realization of the bi-target tracking mobile sensor network, controlled strategies were projected by Su et al. To enhance the tracking quality and maintain network life goals, an idea has been presented based on the non-complete k-covering method Shi et al. A survey has been presented for targeting and tracking issues in heterogeneous environments Sleep et al. and Keskin et al. offered a mathematical model for WSN design decision, data routing, and activity arrangements, and provided two metaheuristic models. Enhanced cluster based multipath routing protocol algorithm in the mobile wireless sensor network (ECBR-WSN) was proposed by Anitha et al., which is dependent on a low energy clustering method. Maximum dump energy, minimum mobility and minimum distance from the base station are considered as the optimizing parameters or fitness functions for the given algorithm that helped to extend the life of wireless sensor network through load balancing node energy consumption. Recently, artificial intelligence-based optimization algorithms got noteworthy attention by scholars for optimizing WSN using various parameters including energy consumption Zhang et al. Han et al. proposed clustering mechanism based on the artificial bee colony algorithm.

3. Hierarchical Scheduling Based Proposed Algorithm in SDN-WSN

In SDN-WSN, hierarchical routing is the combination of local path and global path optimization. Optimal routes can be computed among nodes of the adjacent clusters through local path optimizing and then the global path find can be found using optimization algorithm from target to sink node by a selection of optimal routing among head-to-head clusters. In the process of target tracking, all sensors in WSN are distributed into clusters Zhao et al. An optimal path between the nodes can be passed through the clusters, which can be computed by the optimization algorithm. In this study, the energy consumption (utilization) and throughput is considered as optimization parameters that prolong the lifetime of the proposed SDN-WSN. In SDN-WSN, the programmable SDN controller is responsible for the scheduling optimization algorithm that cuts the operational load over WSN. Although there are many optimization algorithms that are developed for both global and local optimization in SDN-WSN, most of these algorithms pose an exploration/exploitation problem, which generates sub-optimal solutions in the present setup. To address the aforementioned issue, this paper proposes the application specific Dolphin Echolocation Algorithm (DEA) for the optimization of SDN-WSN with respect to the local and global path optimization.

3.1. Problem Formulation in SDN-WSN

For the target-tracking model in SDN-WSN, two parameters (i.e. energy consumption and throughput) will be monitored, where the algorithm will be simultaneously used for both local path and global path optimization. WSN is generally dependent on multi-hop routing technique and is required to construct local routing (LR) between the adjacent clusters. Whereas, starting node N_s in the present cluster $C_s$transmits data through the adjacent clusters C_t to the destination node N_t by using the routing technique. Local routing set as LR ($from\ C_s\ to\ C_t$) can be the optimal path (s) computed by optimization algorithm Zhao et al. As per transmission requirements in WSN, this paper focuses on multi-objective functions with the aim of maximizing throughput and energy consumption efficiency. This consequently results in an increased lifetime of SDN-WSN. For LR the objective function can be formulated as

$Local\ Routing\ Objective\ Function$:

$$LR = max\{\alpha . min\, T(N_s, \dots N_t) + (1 - \alpha)\, min\, E\, (N_s \dots N_t)\} \qquad (1)$$

Where T stands for throughput and E for energy while α is a plenty constant.

At the global level, the routing will involve several clusters. Based on LR, global routing (GR) implements end-to-end routing optimization dependent on service requirements. All computed local paths are segmented into sets such as $P_i \dots P_k$. When the optimization algorithm fulfils the constraint linked with each path; then optimal path(s) is selected for GR. For GR optimization, the objective function can be formulated as

$$Global\ Routing\ Objective\ Function: \qquad max \sum_{P_i}^{P_k} \sum_{Q}^{Q_p} V_{PQ} \qquad (2)$$

Wherein Q is for each path, Q_p is the total number of paths in the P^{th} set, and P_i is each path set in the total number of path sets P_k. V_{PQ} is the function value of Q. GR objective function is to compute the maximum number of optimal paths having maximum throughput and minimum energy utilization. Two constraints are considered here: First is to select the local path from each path set while the other constraint requires that the local paths must be selected from clusters that are either directly or indirectly interconnected.

3.2. Proposed Adaptive Dolphin Echolocation Algorithm for SDN-WSN Optimization

Dolphin Echolocation Algorithm (DEA) is bio-inspired algorithm that mimics the echolocation characteristics of dolphin for prey searching Mosood et al. and Kaveh et al. For the optimization problem described in SDN-WSN in previous sections, the proposed pseudo-code for the proposed algorithm is as follow:

Algorithm. Proposed DEA for SDN-WSN Optimization

1. $\boldsymbol{for}\ number\ of\ iterations\ defined\ for\ the\ algorithm$
2. $\quad \boldsymbol{for}\ each\ echolocation - based\ signal\ (locations)\ as\ variables\ NV$
3. $\quad\quad \boldsymbol{for}\ each\ dimension\ as\ number\ of\ locations\ NL$
4. $\quad\quad\quad compute\ Predefined\ Probability\ (PP)$:

$$PP(loop_i) = PP_1 + (1 - PP_1)\frac{loop_i^{power} - 1}{(total\ number\ of loops)^{power} - 1}$$

$\boldsymbol{end}$
$\boldsymbol{end}$
$\boldsymbol{for}$ $compute$ $\boldsymbol{local\ routing}$ $(\boldsymbol{LR})$ $fitness\ function\ w.r.t\ NL_i$
$LR = \max\{\alpha.\min T(NL_i, \dots NL_m) + (1-\alpha)\min E\ (NL_i \dots NL_m)\}$
$\boldsymbol{if}$
$\boldsymbol{for}$ $each$ $\boldsymbol{LR_i}$
$\boldsymbol{LR_{i_{present}}} \geq \boldsymbol{LR_{i_{presvious}}}$
$Update\ LR_i$
$\boldsymbol{end}$
$\boldsymbol{end}$
$\boldsymbol{end}$
$\boldsymbol{for}$ $compute$ $\boldsymbol{global\ routing}$ $(\boldsymbol{GR})$ $fitness\ function\ w.r.t\ NL_i$
$max \sum_{P_i}^{P_k} \sum_{Q}^{Q_p} V_{PQ}$
$\boldsymbol{end}$
$compute\ accumulative\ fitness\ to\ dolphin\ rules\ w.r.t$ $\boldsymbol{global\ routing}$ $(\boldsymbol{GR - L_{(i,j)}})$
$\boldsymbol{for}\ i = 1{:}\ NL$
$\boldsymbol{for}\ j = 1{:}\ NV$
$find\ the\ optimal\ locations$ $\boldsymbol{GR - L_{(i,j)}}$ $in\ the\ matrix\ of\ and\ specify\ its\ name\ as$ $\boldsymbol{A}$
$take\ range\ of$ $\boldsymbol{-Re\ and\ Re}$ $exploration\ span\ across$ $\boldsymbol{A}$
$\boldsymbol{for}\ k = -Re\ to\ Re$
$evaluate\ Accumulative\ Fitness\ (AF) = 1/Re * (Re - |k|) * optimal\ GR_i + A$
$\boldsymbol{end}$
$\boldsymbol{end}$
$\boldsymbol{end}$
$\boldsymbol{for}$ $each\ NL_i\ based\ on\ optimal\ locations$ $\boldsymbol{GR - L_{(i,j)}}$:
$compute\ optimal\ solution\ with\ minimum$ $\boldsymbol{energy\ consumption}$ $and\ maximum$ $\boldsymbol{throughput}$
$revisit\ the\ rest\ of\ the\ variables (NV_i)\ in\ Accumulative\ fitness\ (AF) = 0$
$\boldsymbol{for}$ $each$ $\boldsymbol{GR - L_{(i,j)}}$
$\boldsymbol{if}$
$\boldsymbol{GR - L_{(i,j)}}_{\boldsymbol{current}} \geq \boldsymbol{GR - L_{(i,j)}}_{\boldsymbol{presvious}}$
$update$ $\boldsymbol{GR - L_{(i,j)}}$
$\boldsymbol{else}$
$compute\ accumulative\ fitness\ to\ dolphin\ rule\ w.r.t$ $\boldsymbol{GR - L_{(i,j)}}$
$\boldsymbol{end}$
$\boldsymbol{end}$
$\boldsymbol{end}$
$For\ j\ variables, compute\ the\ probability\ of\ choosing\ others\ by\ using\ following\ expression;$
$\boldsymbol{for}\ i = 1{:}\ NL$
$\boldsymbol{for}\ j = 1{:}\ NV$

$$P_{ij} = \frac{AF_{ij}}{\sum_{i=1}^{NL} AF_{ij}}$$

$\boldsymbol{end}$
$\boldsymbol{end}$
$update\ PP\ as;$
$\boldsymbol{for}\ i = 1{:}\ NL$
$\boldsymbol{for}\ j = 1{:}\ NV$

```
            if i = The best location(j)
                P_ij = PP
            else
                P_ij = (1 − PP)P_ij
            end
        end
    end
end (repeat the algorithm till the stopping criteria is met)
```

4. Results and Discussion

For experimental setup, MATLAB version R2016a was used for the formulation of introduced mathematical expressions and implementation of the projected algorithm for SDN-WSN optimization. DEA algorithm was then compared with well-known metaheuristic algorithms such as Bat, Ant-colony (ACO) and Grey-Wolf optimization techniques in terms of described optimization problem Masood et al., Kashef et al. and Saxena et al. Results were evaluated into two phases: former part discusses the simulations captured from the MATLAB tool in the form of graphs, while the second part investigates the tables that represent the concise arrangement of additional phases of experiments. The parameters consider for the given experimental setup are shown in Table 1.

Table 1. Parameters in Experiments

Parameter	*Value*
Deployment area	$650m * 650m$
Sensor node model	*Mica Mote*
Node communication range	$120m$
Node location distribution	*uniform*

4.1. MATLAB Simulation Results

In the first experimental phase, 45 sensors and 9 clusters are considered; as each cluster has 5 sensors, whereas the algorithms are applied at LR and GR level. The DEA is scrutinized in comparison to notified algorithms (Bat, ACO and Grey-Wolf) for the given optimization problem. Fig. 1 and Fig. 2 portrays the results obtained for the optimization of SDN-WSN with respect to throughput and energy utilization objective functions. As DEA, Bat, ACO and Grey-Wolf are stochastic nature algorithms. For this reason, the experiments are executed with a method of applying simulations several times, so that each algorithm having 100 iterations will produce an optimal value in one Run. In other words, the algorithms are simulated on MATLAB tool with various number of times, acknowledged as Run, where as the $Mean$ optimal values are computed, based on $Mean$ formula, as shown in Table 2.

In Fig.1 and Fig. 2, the proposed DEA algorithm distinguish itself with better results compared to other stated algorithms in terms of accomplishing maximum throughput and minimum energy utilization. In Fig. 1, DEA produced $Mean$ optimal solutions during each Run interval (from 100 to 2000). The analogous tendency can be monitored in Fig. 2. Consequently, DEA algorithm showed better convergence while successfully engendered optimal solutions of both described objective functions in the given experimental scenario.

In the subsequent phase of the experiment, the proposed DEA and Bat, ACO and Grey-Wolf algorithms are applied on various SDN-WSN network sizes; such as 20, 50 and 80 sensors, along with 4, 10 and 16 clusters, for exploring optimal and worst solutions with respect to throughput and energy consumption objective functions. For throughput, the optimal solutions are maximum values and the worst are minimum throughput values. While, in the case of energy consumption objective function, minimum values are optimal and maximum value is the worst solution, as shown in Tables 3 and 4.

From Table 3 and 4, it is revealed that the proposed DEA algorithm produces the best solutions in comparison with other algorithms for both throughput and energy consumption objective functions. For example, in table 3, for 50 sensors networks, DEA has the optimal solution of 101.200 bps as maximum throughput; whereas, other algorithms generate sub-optimal solutions, which show sub-standard convergence performance of the said techniques. Similarly, in table 4, DEA energy consumptions were the minimum for given network scales. Correspondingly, the DEA algorithm has minimum damage in SDN-WSN network throughput and energy consumption criteria.

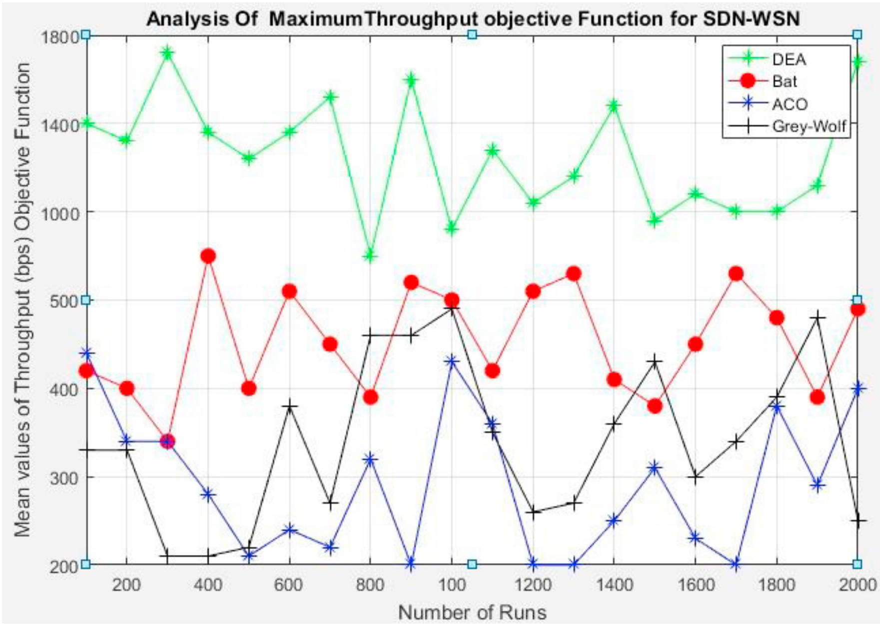

Fig. 1. Analysis of $Mean$ Throughput Objective Function.

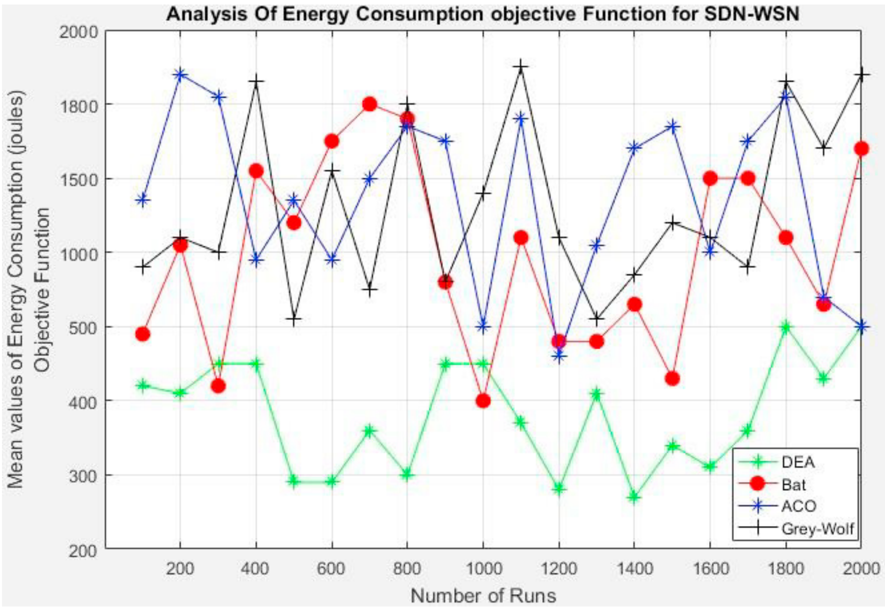

Fig. 2. Analysis of $Mean$ Energy Utilization Objective Function.

Table 2. Experimental Setup

Algorithm	Number of iterations	Number of $Run(s)$	$Mean$ Optimal Values
DEA Bat ACO $Wolf - Grey$	100	100, 200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000, 2000	$\frac{\sum optimal\ values\ in\ each\ Run}{Total\ number\ of\ Runs}$

Table 3. Throughput objective function for SDN-WSN Network

20 Sensors based SDN-WSN for Throughput Objective Function				
	Bat	Grey- Wolf	ACO	DEA
Optimal Solution	263.234 bps	380.112 bps	310.356 bps	956.900 bps
Worst Solution	80.800 bps	220.133 bps	100.313 bps	680.444 bps
50 Sensors based SDN-WSN				
Optimal Solution	381.321 bps	540.200 bps	400.001 bps	901.200 bps
Worst Solution	200.400 bps	320.000 bps	200.300 bps	780.122 bps
80 Sensors based SDN-WSN				
Optimal Solution	450.500 bps	299.810 bps	290.800 bps	899.999 bps
Worst Solution	99.200 bps	110.111 bps	140.300 bps	630.010 bps

Table 4. Energy Consumption objective function for SDN-WSN Network

20 Sensors based SDN-WSN for Energy Consumption Objective Function				
	Bat	Grey-Wolf	ACO	DEA
Optimal Solution	438.082 j	310.111 j	520.190 j	150.100 j
Worst Solution	600.981 j	480.112 j	723.476 j	225.159 j
50 Sensors based SDN-WSN				
Optimal Solution	571.840 j	450.888 j	500.001 j	188.432 j
Worst Solution	761.901 j	555.358 j	666.778 j	290.130 j
80 Sensors based SDN-WSN				
Optimal Solution	400.900 j	399.901 j	333.641 j	175.222 j
Worst Solution	690.123 j	590.378 j	672.441 j	278.992 j

5. Conclusion

The paper focused on the optimization problem of SDN-WSN application and considered throughput and energy utilization of the sensors as parameters. An optimization model is presented, where the SDN-WSN is sliced into LR and GR domains, along with the number of sensors resided in the clusters. With the arranged SDN-WSN optimization model, a meta-heuristic algorithm (i.e. DEA) has offered and designed with its novel pseudo-code specific to the given application. The experiments are conducted in two phases; the former monitors the $Mean$ optimal solutions while implementing the proposed DEA algorithm versus other algorithms (Bat, ACO, Grey-Wolf) several times (100 – 200 $Runs$). The purpose of the experiment was to obtain unambiguous results in the form of $Mean$ values. The experiment disclosed the better performance of DEA algorithm in comparison with the competitive algorithms for the given optimization problem. In order to check the behavior of the algorithm onto various SDN-WSN sizes, second stage experiments are conducted, and results are arranged in table 3 and table 4. Once again, the projected DEA performance is measure with cited algorithms. From the statistics in tables, it is revealed that DEA has not only successfully produced optimal solutions for various SDN-WSN scales but also showed its performance superiority against Bat, ACO and Grey-Wolf algorithms for both objective functions. In other words, for the given scenario, these algorithms had limitations to discover the optimal solution within SDN-WSN. They had generated sub-optimal solutions in both experimental stages. Furthermore, it is also discovered that the network size of SDN-WSN does not disturb the DEA, Bat, ACO and Grey-Wolf algorithm's performance while addressing to the optimization problem.

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