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Statistical Evaluation of Power-Aware Routing Protocols for Wireless Networks:
An Empirical Study

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ABSTRACT

Distributed wireless networks use low-power nodes, battery-powered routers, and base-station nodes. Routing strategies lose energy due to distance-dependent transmission and reception. Researchers design low-power routing solutions for wireless networks. Each technique has unique advantages, restrictions, and research options. Protocols vary in energy consumption, throughput, latency, packet delivery ratio (PDR), scalability, and computational complexity. Researchers can't choose ideal context-aware network models due to diverse performance measurements. This article addresses application-specific deployment strengths to reduce uncertainty. This discussion may help researchers choose context-specific routing models. This article compares power-aware routing model performance measures. This comparison may be used to construct routing models for low-delay, high-throughput, high PDR installations, etc. This paper proposes an algorithm rank score (ARS) with performance metrics. Network designers may employ high-ARS routing models to achieve performance balance over numerous assessments.

KEYWORDS

ARS, Clustering, Delay, Energy, LEACH, Lifetime, PDR, Routing, Statistical, Throughput, Wireless

INTRODUCTION

Routing in wireless networks requires consideration of a wide variety of inter-domain models that include, clustering, geographical node placements, distance evaluation strategies, traffic management, energy considerations, etc. A typical wireless routing model is depicted in Malisetti and Pamula (2020), wherein entire flow of invitation-based routing is visualized. Here, cluster heads (CH) broadcast invitation requests, that contain CH location, energy levels, and other cluster-specific parameters. Nodes respond to these requests with Yes or No acknowledgements, which assist CHs to either accept the nodes or discard them from their cluster lists.

In order to facilitate the transmission of data from one node to another, CHs provide Time Division Multiple Access (TDMA) slots to approved nodes. To complete the node-to-node communication loops, the CHs transmit this information to other nodes or other CHs. In order to execute application-specific routing and communication, models substitute context-specific characteristics like as throughput, PDR, routing overheads, etc. for distance and energy level measurements. In the next part, we'll take a look at some of these models, their intricacies, benefits, and drawbacks, as well as potential directions for future study. To better match current routing models to their deployment

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requirements, researchers may use this topic to suggest the best models for future deployments. To wrap things off, this article makes some intriguing insights about the analyzed models and proposes a variety of ways to enhance their real-time performance.

Researchers have suggested a broad range of low-power routing protocols, each with its own unique benefits, drawbacks, and study areas. Low-energy adaptive clustering hierarchy (LEACH), Hybrid Energy Efficient Distributed Clustering (HEED), Dynamic Clustering and Distance-Aware Routing (DDAR), etc., are only few of the protocols included in this category. In addition, these protocols use numerous machine learning models, such as swarm intelligence, bioinspired computing, neural networks, etc. Other statistical factors, such as energy consumption, communication delays and throughput as well as packet delivery ratio (PDR) and scalability are also different amongst these protocols. It is difficult for researchers and network designers to choose the best models for their context-aware network deployments because of the large range of performance measures. Thus, the motivation & contributions of this text are,

- An in-depth description of these models, together with the application-specific deployment strengths, is provided in this article in an effort to remove this uncertainty. Researchers will be able to narrow down a list of context-specific routing models based on this debate. Besides that, it compares the examined models with other power-aware routing models and assesses their performance on a variety of performance criteria.
- Researchers and network designers will be able to find routing models that are most suited for installations requiring features such as low latency, high throughput, high PDR, etc., after consulting this comparison.
- This paper also proposes a new algorithm rank score (ARS), which incorporates a variety of assessment indicators to provide a more complete picture of performance. Selecting routing models with high ARS performance allows network designers to implement routing models that maintain performance equilibrium throughout a variety of simulations and tests.

Based on these contributions, readers will be able to identify optimal models for their application-specific & performance-specific deployments.

LITERATURE REVIEW

A wide variety of low power routing models are proposed by researchers over the years, and each of these models vary in terms of energy efficiency, routing delay, throughput, and other network related parameters. These models propose a set of optimization techniques, which assist in identification of suitable network parameters for high-efficiency route selections. For instance, work in Malisetti and Pamula (2020) proposes a quasi-oppositional butterfly optimization model (QOBOM) which assists in selection of cluster heads in heterogeneous sensor networks. It introduces a quasi-distance & energy metric variable during selection of cluster heads which assists in reducing energy consumption during network communications. The QOBOM method outperforms LEACH, Enhanced LEACH (ELEACH), Particle Swarm Optimization based clustering (PSOC), and Butterfly Optimization Model (BOM) in terms of overall network lifetime, but has higher computational complexity, which increases delay and reduces throughput in real-time deployments. To overcome this limitation, work in R. R. A. et al. (2019) proposes design of Cuckoo Search Optimization (CSO) Model that is validated for Rescue and Emergency Mobile Ad-hoc Networks (MANETs). Flow of the proposed CSO Model is depicted in R. R. A. et al. (2019), wherein it can be observed that initially an improved LEACH (I LEACH) model is used to cluster nodes into low, medium & high distance clusters. These clusters are processed via ICSO (improved CSO) model, which assists in shortest path selection and high-efficiency packet transmissions. The model showcases lower delay, and better energy efficiency when compared with

Hybrid Ant Colony Optimization (ACO) with Multiple Objective Genetic Algorithm (MGA), and Fuzzy Aided ACO (FACO), but has higher complexity than both the models.

Large-scale Internet of Things (IoT) and Vehicular Ad-hoc Networks cannot benefit from the ICSO model's increased complexity (VANETs). Chithaluru et al. (2021) discusses a simplified LEACH model that makes use of energy-enhanced threshold routing, in which researchers have estimated energy threshold levels by selecting forwarding nodes. There are opportunistic forwarders nodes that can help reduce the amount of energy required for inter-node data transfers. Comparing the model's energy performance to other LEACH algorithms, such as Quadrature LEACH, Node Ranked LEACH, and LEACH with GA and PSO, it is shown to be superior, making it an excellent choice for real-time network application situations. LEACH MTC (LEACH with Moving Target Constraint) is mentioned in (Fu et al., 2021) to help with Cluster Head selection even in settings with moving nodes, which further improves the performance of this model. For estimating the elliptical monitoring area and node movement directions, it makes use of an extended Kalman filter (EKF). It has a longer lifespan than the LEACH DBCH and LEACH RARE models, which use a distance-based cluster head. Using a mix of multiple LEACH-based optimization models, researchers describe similar models in Devika et al. (2021); Cui et al. (2019), where PSO with Wolf Search Optimization (WSO) and PSO with Weighted Harmonic Centroid based Bat Optimization (PSO WHCBO) Methods are presented. There are a variety of fitness functions that take into account energy consumption as well as internode and intra-cluster distances, for example. Because of this, the model uses stochastic evaluations to choose the best nodes to utilize as cluster heads in routing and data transfer situations. Loganathan and Arumugam (2021) discusses a review of several PSO models, including Elephant Herding Optimization (EHO), Bacterial Foraging Optimization (BFO), Grey Wolf Optimization (GWO), and Firefly Optimization (FFO), and comes to the conclusion that PSO-based models beat the competition. When creating energy-conscious, distance-conscious, and QoS-aware clustering optimized network applications, PSO should be implemented. Other bioinspired models have been developed by researchers to aid in the deployment of low-complexity and high-throughput energy-efficient network installations, similar to PSO. According to Bhola et al. (2019), a model like this is presented using GA-based LEACH, which focuses on residual energy and the number of nodes utilized during communication to determine route. When it comes to low-power and delay-aware communication, work in Nigam and Dabas (2021) suggests the use of PSO with k Means for clustering nodes at the node level. Based on intra cluster distances, node-to-base station distances, and residual energy levels, the EPSO (Extended PSO) model proposes a dynamic fitness function. However, the model's increased complexity causes computational delays for large-scale network installations while also improving QoS performance over the original LEACH model.

Fuzzy logic with a competition radius is proposed in Adnan et al. (2021) as a way to minimize computing complexity when picking cluster heads. In order to maintain the network model's QoS heterogeneity, these clusters comprise nodes with varying distances, residual energies, throughputs, and packet delivery ratios (PDRs). For example, the model is able to find cluster heads capable of communicating across short distances with high residual energy and a large number of nodes. This helps to cut down on energy waste and so extend the lifespan of networks at a medium to large scale. For energy efficiency, this model surpasses the EAMMH, TTDFP, and Energy-Aware Unequal Clustering Fuzzy (EAUCF) approaches. However, it does not take into account other QoS metrics like routing efficiency, network overhead, etc. when CH choices. Because of this, its use is restricted to small and medium-sized networks. Remaining energy levels and resilient routing may be considered in the usage of Artificial Neural Network (ANN) and Learning Automata for Multilevel Heterogeneous Network Routing (LA MHNR) in wireless networks to solve this constraint. Using spectrum sharing and continuous learning, these models seek to maximize network longevity while reducing computing costs. Like the REM LEACH and centralized energy-efficient clustering routing models (CEECR) presented in Aydin et al. (2021); J. Zhang and Yan (2019), researchers have expanded LEACH by using Mobile Receiver Selective Path Priority with residual energy maximization (REM LEACH) and a centralized clustering routing model (CEECR). Large-scale homogeneous networks may use these models because of their low computing cost; however, heterogeneous networks cannot. Using a unique fitness function that integrates residual node energy levels with distance measurements and node density metrics, the work in C. Wang et al. (2020) suggests a Chaotic Genetic Algorithm (CGA) Model to solve this constraint. Evaluation of this fitness function can be done via equation 1, wherein multiple tunable factors ($\partial, \varnothing, \text{ and } \alpha$) are used to control efficiency of selected cluster heads and routing paths.

$$\mathrm{Novel}\left(\mathrm{F}\right) = \partial * \frac{\mathrm{E_T} - \mathrm{E_D}}{\mathrm{E_T}} + \varnothing * \frac{\mathrm{DNB} - \mathrm{DN}}{\mathrm{DNB}} + \alpha * \frac{\mathrm{NN} - \mathrm{NC}}{\mathrm{NN}} \tag{1}$$

where, $\mathrm{E_T}$, $\mathrm{E_D}$, DNB, DN, NN and NC represents total energy levels, Nodes in a network are divided into clusters based on their distance from a base station, inter-node distance, total amount of wasted energy, and so on. A broad range of real-time deployments may benefit from this model's superior performance, since it outperforms a number of current techniques. R LEACH with a caching technique and DCBSRP have been presented as extensions to these models in Y. Zhang et al. (2021); Adil et al. (2020) by researchers. Using caching and distance thresholding, these models help to reduce a network overhead, which tries to improve energy efficiency by minimizing inter-node distance during communications through caching. Because of their ability to continuously evaluate parameters; these models are well-suited for usage with high-performance computer nodes. Because of this, they cannot be utilized for broad purpose wireless sensor applications. This model's scalability may be improved by using the Layered and Heterogeneous Routing (LHR) Model, which uses clustering of nodes based on stochastic energy. Nodes are separated into 'normal' and 'advanced' clusters as a result of this clustering process, making it easier for the model to choose cluster heads with a low level of complexity. Similar techniques for dynamic threshold-based clustering that attempt to minimize network redundancy during cluster head selection use energy-efficient scalable routing (EESR) with multiple hop communications (Ahmed Elsmany et al., 2019) and probabilistic perception layer (PPL) (Xu et al., 2019). They must be tested in bigger network contexts and expanded using bioinspired models like the Modified African Buffalo with Group Teaching Optimization (MAB GTO) (B. A. et al., 2021). These fitness functions are regularly updated to help in the dynamic selection of cluster heads, as represented in Figure 4 of this model. Flow of this model is Xu et al. (2019) Compared to LEACH, this model is more energy efficient and has a greater throughput; however the intricacy of this model makes it more difficult to implement and computationally slow. As a result of this continual selection of clusters, the model has a greater packet delivery ratio (PDR) performance.

Reinforcement Learning (RL) and ERQTM (Energy efficient Routing with QoS-supported Traffic Management) are two examples of similar models that have been presented by researchers (C. C. Wang et al., 2020) (Samarji & Salamah, 2021). The MDRM and ERQTM models provide improved network performance under real-time situations, making them ideal for large-scale network installations. Researchers have recommended the usage of Energy-aware Routing Protocol with delay awareness (ERP DA) and Energy Harvesting Intelligent Relay Selection Protocol (EH-IRSP) for low-delay and high-throughput applications in (Liu et al., 2021) (Khan et al., 2021). Researchers have discussed the use of Q-Learning-Based Data-Aggregation-Aware Energy-Efficient Routing Protocol (Q DAA EERP), Connectivity and Energy Aware Layering Routing (CELR), Energy-Aware Geographic Routing (EAGR), Energy and Collision Aware WSN Routing Protocol (ECARP), and EERP with discrete points of interest (DPOI) for 3D network scenarios (Yun & Yoo, 2021) (Han et al., 2021) (Sangaiah et al., 2021) (Patel et al., 2021). Energy-based routing and machine learning approaches for reducing computational redundancy are included in these models, which help to create high-efficiency and low-power routing models.

Work in Jurado-Lasso et al. (2021); Rathee et al. (2021) proposes the usage of SDM WSN and ACO QEBSR, both of which enable network designers to fine-tune clustering and routing processes. Joint Topology Construction with Hybrid Routing Strategy (JTC HRS) and the Destination Oriented Routing Algorithm (DORA) are proposed for large-scale network applications in Yu et al. (2021); K. Wang et al. (2021) as possible solutions to this problem. For routing and communication reasons, both of these models use several distance metrics and Quality of Service (QoS) criteria to identify high-performance nodes. These models' extensions include Wireless Energy Balancers (WEBs) Alabdali et al. (2021), Compressive Sensing (CS) Lin et al. (2021), Balanced Residual Energy (BRE) with LEACH Daanoune et al. (2019), Assistant Cluster Heads (ACHs) based on LEACH Kumar et al. (2020), and Multiple Weight (MW) LEACH (el Khediri et al., 2020). Each of these models works by selecting multiple routing nodes with backup provisioning to help with fault tolerance in practical routing scenarios. These models enhance network performance, but they diminish the efficiency of node use since the backup nodes are typically inactive and only communicate when the main nodes have problems. There must be stochastic optimization approaches that are able to discover idle nodes and use their computing and routing skills in order to overcome this barrier. The use of Slime Mould Algorithm (SMA) with LEACH, improved clustering dynamic threshold (ICD) with k Means for energy-based clustering, and Energy efficient Least Edge Computation routing protocol (ELEC) for improving node efficiency during network communications are three examples of such models discussed in (Thi Quynh & Viet, 2021) (Ding et al., 2021). It is possible to identify nodes that may be utilized for residual communications using these models. These residual nodes use Time Division Multiple Access (TDMA), allowing for communication and backup. Researchers have suggested ways to improve continuous performance by extending existing models, such as the TLCM (two-level clustering mechanism) Bany Salameh et al. (2021), the PE-LEACH (partitioned-based energy-efficient – LEACH) Mohapatra and Rath (2019), and the LMNN LEACH (Levenberg-Marquardt Neural Network-based LEACH) (Mittal et al., 2020). In order to improve their long-term network performance, these models strive to learn iteratively via regular checks on energy use. As a result, academics have developed a broad range of clustering models, each with its own set of machine learning-based optimization features. In the following portion of this article, the models' performance is evaluated in terms of energy efficiency, computational complexity, fault tolerance, scalability, and QoS performance.

PERFORMANCE EVALUTION & COMPARISION

A thorough examination of several energy efficient wireless network models reveals a wide range of implementations, applications, and performance measurements for these systems. For the purpose of evaluating this performance, this section compares models based on their energy efficiency, computational complexity, fault tolerance, scalability, and quality of service performance, and then fuzzified these metrics into Fuzzified Low Range (FLR), Fuzzified Medium Range (FMR), Fuzzified High Range (FHR), and Fuzzified Very High Range (FVHR) ranges. These metrics are then used to calculate the performance of each model. Comparing evaluated models on a single quantifiable scale makes it easier for readers to see how they perform in various network circumstances after the fuzzification process. Readers will be able to compare node-level and network-level data, as shown in Table 1, as a result of this comparison.

Based on this evaluation, and figure 1., it can be observed that BOM (Malisetti & Pamula, 2020), ICD (Ding et al., 2021), QOBOM (Malisetti & Pamula, 2020), E LEACH (Malisetti & Pamula, 2020), PSOC (Malisetti & Pamula, 2020), FACO (R. R. A. et al., 2019), and Q LEACH (Chithaluru et al., 2021) have lowest computational complexity, thus can be used with networks that require low-overhead communication interfaces.

Similarly, by referring Table 1 and figure 2., it can be observed that Adaptive Rank (Chithaluru et al., 2021), EAMMH (Adnan et al., 2021), ANN (Mehmood et al., 2020), REM LEACH (Aydin et

Table 1. Performance evaluation of different energy aware protocols

Model	Computational Complexity	Energy Efficiency	Fault Tolerance	Quality of Service Performance	Scalability
QOBOM (Malisetti & Pamula, 2020)	FMR	FHR	FLR	FMR	FLR
E LEACH (Malisetti & Pamula, 2020)	FMR	FMR	FLR	FMR	FLR
PSOC (Malisetti & Pamula, 2020)	FMR	FMR	FLR	FMR	FMR
BOM (Malisetti & Pamula, 2020)	FLR	FMR	FLR	FMR	FMR
ICSO LEACH (R. R. A. et al., 2019)	FHR	FMR	FMR	FMR	FLR
ACO MGA (R. R. A. et al., 2019)	FVHR	FMR	FMR	FHR	FMR
FACO (R. R. A. et al., 2019)	FMR	FHR	FLR	FMR	FLR
Adapt. Rank (Chithaluru et al., 2021)	FHR	FVHR	FMR	FHR	FMR
Q LEACH (Chithaluru et al., 2021)	FMR	FMR	FMR	FHR	FLR
NR LEACH (Chithaluru et al., 2021)	FMR	FMR	FHR	FMR	FHR
GA LEACH (Chithaluru et al., 2021)	FHR	FHR	FHR	FMR	FMR
PSO LEACH (Chithaluru et al., 2021)	FHR	FMR	FLR	FMR	FHR
LEACH MTC (Fu et al., 2021)	FHR	FHR	FHR	FMR	FVHR
PSO WSO (Devika et al., 2021)	FVHR	FHR	FLR	FHR	FHR
PSO WHCBO (Cui et al., 2019)	FVHR	FHR	FMR	FHR	FMR
GA LEACH (Bhola et al., 2019)	FHR	FHR	FLR	FMR	FMR
EPSO (Nigam & Dabas, 2021)	FHR	FMR	FMR	FLR	FMR
Fuzzy LEACH (Adnan et al., 2021)	FMR	FHR	FLR	FHR	FLR
EAMMH (Adnan et al., 2021)	FVHR	FVHR	FMR	FHR	FVHR
TTDFP (Adnan et al., 2021)	FHR	FHR	FHR	FHR	FVHR
EAUCF (Adnan et al., 2021)	FHR	FHR	FMR	FMR	FHR
ANN (Mehmood et al., 2020)	FVHR	FVHR	FMR	FHR	FHR
LA MHNR (Tanwar et al., 2019)	FVHR	FHR	FHR	FHR	FHR
REM LEACH (Aydin et al., 2021)	FMR	FVHR	FMR	FHR	FHR
CEECR (J. Zhang & Yan, 2019)	FMR	FHR	FMR	FHR	FHR
CGA (C. Wang et al., 2020)	FVHR	FHR	FHR	FHR	FHR
R LEACH (Y. Zhang et al., 2021)	FHR	FHR	FMR	FMR	FHR
DCBSRP (Adil et al., 2020)	FHR	FVHR	FMR	FHR	FHR
LHR (Huo et al., 2020)	FMR	FHR	FLR	FHR	FMR
EESR (Ahmed Elsmany et al., 2019)	FVHR	FHR	FLR	FHR	FVHR
PPL (Xu et al., 2019)	FHR	FHR	FMR	FHR	FMR
MAB GTO (B. A. et al., 2021)	FVHR	FHR	FMR	FVHR	FHR
MDRM RL (C. C. Wang et al., 2020)	FVHR	FVHR	FMR	FHR	FHR
ERQTM (Samarji & Salamah, 2021)	FHR	FHR	FMR	FHR	FMR
ERP DA (Liu et al., 2021)	FHR	FHR	FLR	FHR	FHR
EH IRSP (Khan et al., 2021)	FVHR	FHR	FMR	FHR	FMR
Q DAA EERP (Yun & Yoo, 2021)	FVHR	FVHR	FHR	FHR	FHR
CELR (Han et al., 2021)	FHR	FHR	FHR	FMR	FMR

Model	Computational Complexity	Energy Efficiency	Fault Tolerance	Quality of Service Performance	Scalability
EAGR (Sangaiah et al., 2021)	FHR	FMR	FHR	FMR	FHR
ECARP (Patel et al., 2021)	FHR	FHR	FHR	FMR	FHR
EERP DOI (Xu et al., 2021)	FVHR	FMR	FMR	FHR	FLR
SDM WSN (Jurado-Lasso et al., 2021)	FMR	FHR	FHR	FMR	FHR
ACO QEBSR (Rathee et al., 2021)	FHR	FVHR	FMR	FHR	FHR
JTC HRS (Yu et al., 2021)	FVHR	FHR	FMR	FHR	FHR
DORA (K. Wang et al., 2021)	FMR	FHR	FMR	FMR	FHR
WEBs (Alabdali et al., 2021)	FMR	FVHR	FLR	FMR	FLR
CS (Lin et al., 2021)	FMR	FHR	FMR	FLR	FMR
BRE LEACH (Daanoune et al., 2019)	FHR	FHR	FLR	FHR	FMR
ACHs (Kumar et al., 2020)	FMR	FHR	FHR	FMR	FHR
MW LEACH (el Khediri et al., 2020)	FHR	FVHR	FMR	FHR	FHR
SMA LEACH (Thi Quynh & Viet, 2021)	FHR	FHR	FMR	FHR	FMR
ICD (Ding et al., 2021)	FLR	FMR	FMR	FHR	FMR
ELEC (Us Sama et al., 2020)	FVHR	FVHR	FLR	FHR	FMR
TLCM (Bany Salameh et al., 2021)	FHR	FHR	FMR	FHR	FMR
PE LEACH (Mohapatra & Rath, 2019)	FHR	FVHR	FHR	FMR	FHR
LMNN LEACH (Mittal et al., 2020)	FVHR	FVHR	FVHR	FHR	FHR

Figure 1. Computational complexity of different models

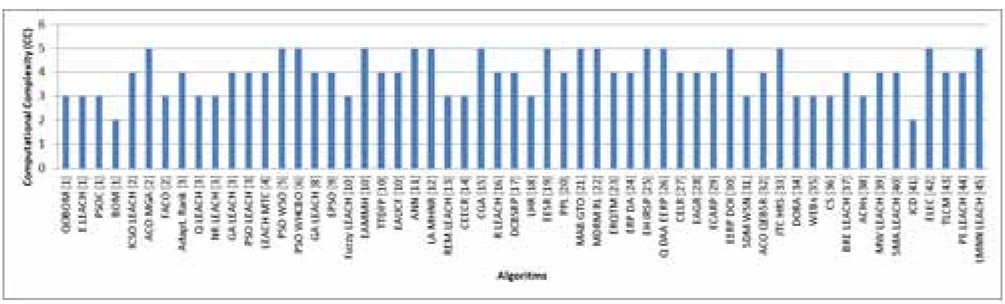
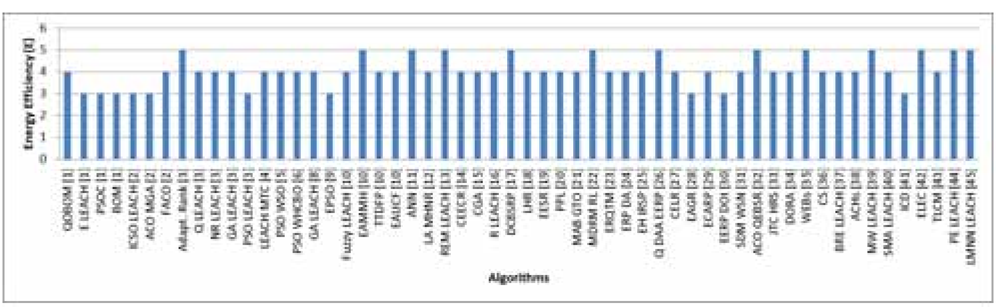


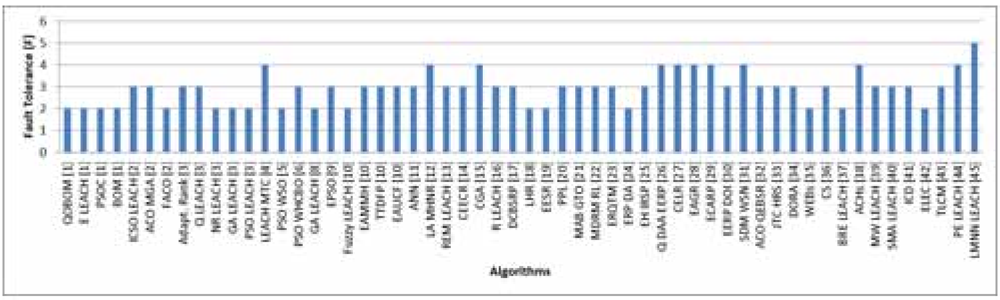
Figure 2. Energy Efficiency of different models



al., 2021), DCBSRP (Adil et al., 2020), MDRM RL (C. C. Wang et al., 2020), Q DAA EERP (Yun & Yoo, 2021), ACO QEBSR (Rathee et al., 2021), WEBs (Alabdali et al., 2021), MW LEACH (el Khediri et al., 2020), ELEC (Us Sama et al., 2020), PE LEACH (Mohapatra & Rath, 2019), and LMNN LEACH (Mittal et al., 2020) have highest energy efficiency, and thus must be used for low-power and high lifetime network deployments. These models must be combined to form hybrid energy aware interfaces.

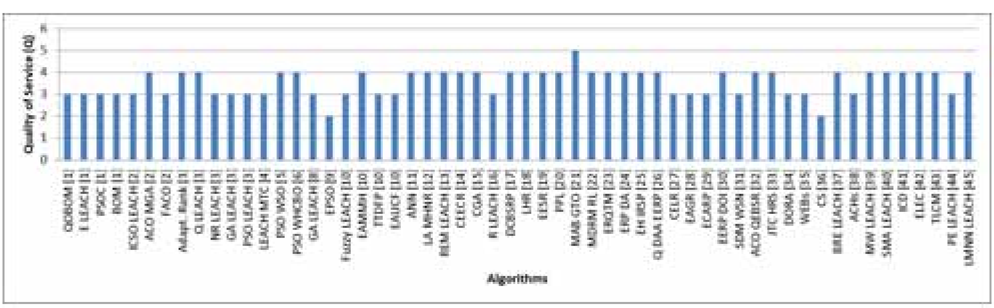
Similarly, from Table 1 and figure 3., it can be observed that LMNN LEACH (Mittal et al., 2020), LEACH MTC (Fu et al., 2021), LA MHNR (Tanwar et al., 2019), CGA (C. Wang et al., 2020), Q DAA EERP (Yun & Yoo, 2021), CELR (Han et al., 2021), EAGR (Sangaiah et al., 2021), ECARP (Patel et al., 2021), SDM WSN (Jurado-Lasso et al., 2021), ACHs (Kumar et al., 2020), and PE LEACH (Mohapatra & Rath, 2019) have highest fault tolerance performance, thereby making them useful for energy efficient, and secure routing scenarios.

Figure 3. Fault tolerance performance of different models



Based on Table 1 and figure 4., it can also be observed that MAB GTO (B. A. et al., 2021), ACO MGA (R. R. A. et al., 2019), Adaptive Rank (Chithaluru et al., 2021), Q LEACH (Chithaluru et al., 2021), PSO WSO (Devika et al., 2021), PSO WHCBO (Cui et al., 2019), EAMMH (Adnan et al., 2021), ANN (Mehmood et al., 2020), LA MHNR (Tanwar et al., 2019), REM LEACH (Aydin et al., 2021), CEECR (J. Zhang & Yan, 2019), CGA (C. Wang et al., 2020), DCBSRP (Adil et al., 2020), LHR (Huo et al., 2020), EESR (Ahmed Elsmany et al., 2019), PPL (Xu et al., 2019), MDRM RL (C. C. Wang et al., 2020), ERQTM (Samarji & Salamah, 2021), ERP DA (Liu et al., 2021), EH IRSP (Khan et al., 2021), and Q DAA EERP (Yun & Yoo, 2021) have better QoS than other models, and thus can be used for high-performance communication interfaces.

Figure 4. QoS performance of different models



Also, by referring Table 1 and figure 5., it can be observed that LEACH MTC (Fu et al., 2021), EAMMH (Adnan et al., 2021), TTDFP (Adnan et al., 2021), EESR (Ahmed Elsmany et al., 2019), NR LEACH (Chithaluru et al., 2021), PSO LEACH (Chithaluru et al., 2021), PSO WSO (Devika et al., 2021), EAUCF (Adnan et al., 2021), ANN (Mehmood et al., 2020), LA MHNR (Tanwar et al., 2019), REM LEACH (Aydin et al., 2021), CEECR (J. Zhang & Yan, 2019), CGA (C. Wang et al., 2020), and R LEACH (Y. Zhang et al., 2021) have better scalability performance than other models, thereby making them useful for large-scale deployment scenarios. But these individual evaluations will assist readers to identify single parameter optimized models.

Figure 5. Scalability performance of different models

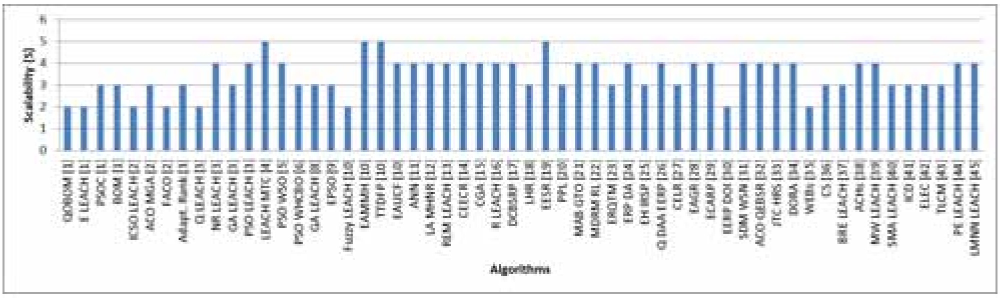
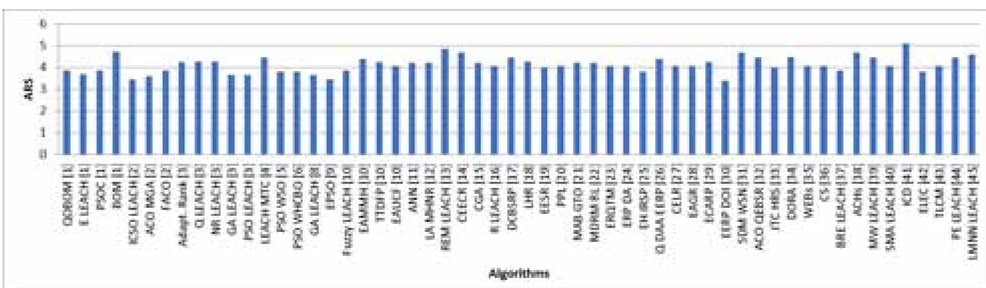


Figure 6. ARS performance of different models



To further facilitate model evaluation, all the parameters are combined to form an algorithmic rank score (ARS), which can be evaluated via equation 2 as follows,

$$ARS = \frac{5}{CC} + \frac{E}{5} + \frac{F}{5} + \frac{Q}{5} + \frac{S}{5} \ldots (2)$$

Based on this score, rank is evaluated for all models, and can be observed from Table 2 as follows,

Table 2. ARS performance of different models

Rank	Model	ARS
1	ICD (Ding et al., 2021)	5.10
2	REM LEACH (Aydin et al., 2021)	4.87
3	BOM (Malisetti & Pamula, 2020)	4.70
4	CEECR (J. Zhang & Yan, 2019)	4.67
5	SDM WSN (Jurado-Lasso et al., 2021)	4.67
6	ACHs (Kumar et al., 2020)	4.67
7	LMNN LEACH (Mittal et al., 2020)	4.60
8	DORA (K. Wang et al., 2021)	4.47
9	DCBSRP (Adil et al., 2020)	4.45
10	ACO QEBSR (Rathee et al., 2021)	4.45
11	MW LEACH (el Khediri et al., 2020)	4.45
12	PE LEACH (Mohapatra & Rath, 2019)	4.45
13	LEACH MTC (Fu et al., 2021)	4.45
14	EAMMH (Adnan et al., 2021)	4.40
15	Q DAA EERP (Yun & Yoo, 2021)	4.40
16	Q LEACH (Chithaluru et al., 2021)	4.27
17	NR LEACH (Chithaluru et al., 2021)	4.27
18	LHR (Huo et al., 2020)	4.27
19	Adapt. Rank (Chithaluru et al., 2021)	4.25
20	TTDFP (Adnan et al., 2021)	4.25
21	ECARP (Patel et al., 2021)	4.25
22	ANN (Mehmood et al., 2020)	4.20
23	LA MHNR (Tanwar et al., 2019)	4.20
24	CGA (C. Wang et al., 2020)	4.20
25	MAB GTO (B. A. et al., 2021)	4.20
26	MDRM RL (C. C. Wang et al., 2020)	4.20
27	WEBs (Alabdali et al., 2021)	4.07
28	CS (Lin et al., 2021)	4.07
29	EAGR (Sangaiah et al., 2021)	4.05
30	EAUCF (Adnan et al., 2021)	4.05
31	R LEACH (Y. Zhang et al., 2021)	4.05
32	PPL (Xu et al., 2019)	4.05
33	ERQTM (Samarji & Salamah, 2021)	4.05
34	ERP DA (Liu et al., 2021)	4.05
35	CELR (Han et al., 2021)	4.05
36	SMA LEACH (Thi Quynh & Viet, 2021)	4.05
37	TLCM (Bany Salameh et al., 2021)	4.05
38	EESR (Ahmed Elsmany et al., 2019)	4.00
39	JTC HRS (Yu et al., 2021)	4.00

Rank	Model	ARS
40	QOBOM (Malisetti & Pamula, 2020)	3.87
41	PSOC (Malisetti & Pamula, 2020)	3.87
42	FACO (R. R. A. et al., 2019)	3.87
43	Fuzzy LEACH (Adnan et al., 2021)	3.87
44	BRE LEACH (Daanoune et al., 2019)	3.85
45	PSO WHCBO (Cui et al., 2019)	3.80
46	EH IRSP (Khan et al., 2021)	3.80
47	ELEC (Us Sama et al., 2020)	3.80
48	PSO WSO (Devika et al., 2021)	3.80
49	E LEACH (Malisetti & Pamula, 2020)	3.67
50	PSO LEACH (Chithaluru et al., 2021)	3.65
51	GA LEACH (Chithaluru et al., 2021)	3.65
52	GA LEACH (Bhola et al., 2019)	3.65
53	ACO MGA (R. R. A. et al., 2019)	3.60
54	ICSO LEACH (R. R. A. et al., 2019)	3.45
55	EPSO (Nigam & Dabas, 2021)	3.45
56	EERP DOI (Xu et al., 2021)	3.40

Based on this evaluation and figure 6 it can be observed that ICD (Ding et al., 2021), REM LEACH (Aydin et al., 2021), BOM (Malisetti & Pamula, 2020), CEECR (J. Zhang & Yan, 2019), SDM WSN (Jurado-Lasso et al., 2021), ACHs (Kumar et al., 2020), LMNN LEACH (Mittal et al., 2020), DORA (K. Wang et al., 2021), DCBSRP (Adil et al., 2020), ACO QEBSR (Rathee et al., 2021), MW LEACH (el Khediri et al., 2020), PE LEACH (Mohapatra & Rath, 2019), LEACH MTC (Fu et al., 2021), EAMMH (Adnan et al., 2021), and Q DAA EERP (Yun & Yoo, 2021) have better overall performance, and can be used for high energy efficiency, low complexity, high fault tolerance, high QoS and high scalability application scenarios.

CONCLUSION AND FUTURE WORK

This comprehensive examination of several energy-conscious routing models for wireless networks shows that LEACH-based solutions outperform their competition. CH routing nodes are selected based on their energy levels. PSO-based LEACH, GA-based LEACH and other bioinspired models are examples of LEACH variants that are more energy efficient. In terms of computing complexity, these models were found to be BOM, ICD, QOBOM, E LEACH, PSOC, FACO, and Q LEACH. The models with the maximum energy efficiency, such as ACOs, WEBs and MW LEACH, may be employed for low-power wireless sensor networks. The maximum fault tolerance has been found in the LMNN LEACH, LEACH MTC, LA MHNR, CGA, Q DAA EERP, CELR, EAGR, ECARP, SDM, WSN, ACHs, and PE LEACH models, while the QoS of the MAB, GTO, ACO, MGA, Adaptive Rank, Q LEACH models, PSO WSO models, PSO WHCBO models, EAMMH models, ANN, LA These models must be integrated to produce high QoS and superior fault tolerance performance under varied network scenarios. All these metrics were combined to form an Algorithmic Rank Score, which indicated that ICD, REM, BOM CEECR, SDM, WSN and the like had better overall performance and could be used for high energy efficiency, low complexity high fault tolerance, high QoS and high scalability application scenarios, such as high-energy efficiency low complexity, high fault tolerance high QoS, and high scalability applications. To increase network performance in real-time deployment settings, researchers may mix these models in the future to produce hybrid LEACH approaches that should deliver higher lifespan with high QoS performance under multiple use cases.

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