© September 2021| IJIRT | Volume 8 Issue 4 | ISSN: 2349-6002

Statistical evaluation of energy harvesting system models in wireless networks: An empirical perspective

Jaya Dipti Lal[1], Dr Dolly Thankachan[2]
[1]Assistant Professor, Electronics & Tc Department, S.G.S.I.T.S. Indore (MP), PhD Scholar, Oriental University Indore (M.P.)
[2]Associate Professor and Head, Department of Electrical and Electronics Engineering Oriental University Indore (M.P.)

***Abstract* - Energy harvesting is a traditional concept, which is used by a wide variety of physical systems for converting naturally available energy into electric power. Sources of power include wind, solar, mechanical vibrations, magnetic fields, temperature variations, application specific power transforming sources, etc. Wireless sensor networks (WSNs) consist of a wide variety of limited power nodes, each of which continuously require energy for operation. These nodes are placed at remote locations, due to which continuous physical monitoring is not possible. This limits the capability to replace power sources (batteries) for these nodes, thus affecting their normal functioning. As an alternate to power source replacement, wireless network researchers have proposed use of energy harvesting in wireless sensor nodes. In order to perform this task, a wide variety of energy harvesting models are proposed by researchers, each of which vary in terms of computational complexity, harvesting efficiency, energy efficiency, and size of harvesting models. Due to which it becomes difficult for network designers to select the best possible energy harvesting model for their deployments. To reduce this difficulty of model selection, this text reviews a wide variety of network models directed at energy harvesting. These models are compared in terms of deployment application type, energy efficiency, computational complexity, etc. Upon referring this comparison, researchers and network designers can select the best suited model for their deployment, which will assist in improving network lifetime and harvesting performance. Moreover, this text also proposes various model level enhancements which will assist in improving performance of already defined energy harvesting techniques. This text also performs application wise statistical comparison of reviewed models, which further assists in selecting deployment specific models for highly effective network design.**

***Index Terms* - Energy, harvesting, sensor, renewable, lifetime, computational complexity.**

INTRODUCTION

Optimizing battery utilization is a major task for any wireless sensor network (WSN). To achieve this task, a wide variety of models are developed, which include sleep scheduling, duty cycle optimization, node-to-node load balancing, distributed computing, etc. But due to limited battery capacity and physical access limitations, WSN nodes often require frequent battery replacement, which reduces their long-term running efficiency. To reduce the probability of battery replacement, various energy harvesting circuits are integrated into wireless nodes [1]. These circuits convert renewable energy sources like solar energy, wind energy, temperature variations, mechanical disturbances, etc. into electrical energy. This converted energy is used to charge the power source connected wireless sensor node. Additionally, some wireless networks, as depicted in figure 1, offload computationally complex tasks to high energy nodes, in order to extend network lifetime, thereby improving their battery capacity.

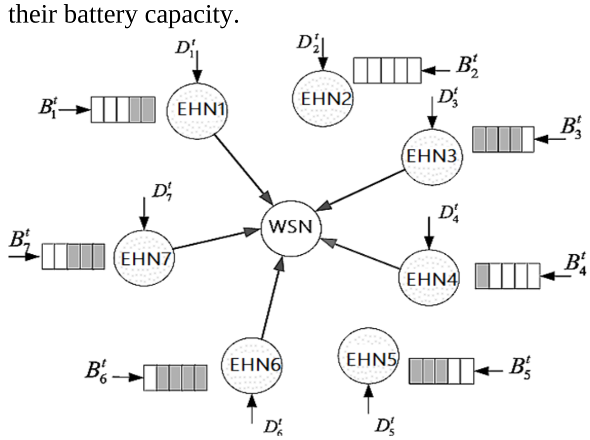


Figure 1. Wireless sensor network with energy harvesting

From the network model it can be observed that each energy harvesting node (EHN) has a battery source, and an energy harvesting circuit. This circuit is responsible for converting renewable source energy into electrical power for charging the battery. The EHNs estimate their battery power, and offload their computationally complex tasks to the wireless sensor node (WSN) showcased at the centre. This process enhances energy efficiency of the offloading node, thereby giving it more time for external charging. Approaches similar to this are proposed by researchers, and vary in terms of energy efficiency, computation complexity, and other parameters. A survey of these approaches can be observed from the next section, along with their nuances, advantages, limitations and characteristics. This is followed by performance evaluation of the reviewed algorithms, along with their statistical comparison in terms of empirical parameters. By referring to this comparison, researchers can identify the best possible energy harvesting algorithm(s) for their deployments. Finally, this text concludes with some interesting observations about the reviewed algorithms and recommends methods to improve it.

LITERATURE REVIEW

Harvesting energy in wireless sensor networks requires design of inherently efficient models that allow for low energy operations. For instance, the work in [2] proposes a low energy clustering model that uses solar energy for harvesting. Components like solar plate, harvesting module device, and storage device are used in order to harvest solar power. The harvested power is represented using equation 1 as follows,

$$P_{harvest}(t) = P_{battery}(t+1) - P_{battery}(t) + P_{active}(t) + P_{sleep}(t) \ldots (1)$$

Where, $P_{harvest}, P_{battery}, P_{active}, and\ P_{sleep}$ represent harvested, battery, active and sleep power levels. The model further utilizes a specialized frame structure that supports EH model, wherein the following parameters are stored on the frame, and communicated throughout network,

- Shared information between nodes
- Distance calculations between nodes
- Radius calculation for clustering
- Cluster head selection information
- Cluster formation details
- Node identification number
- Rate of energy harvesting
- Residual energy in the nodes

Decisions about clustering, and harvesting are taken based on these parameters. The proposed novel energy harvesting clustering protocol (NEHCP) is found to have 71% energy efficiency, which is higher than sleep awake energy-efficient distributed (SEED) that has an efficiency of 61.8%, hybrid unequal clustering layering protocol (HUCL) that has an efficiency of 45.7% and centralized energy-efficient cluster (CEEC) that has an efficiency of 37.7% on the same network conditions. This efficiency can be improved with energy prediction systems, which can pre-emptively decide which nodes should be given more power, while which nodes must be put to sleep mode, depending upon their behavioural patterns. The work in [3] proposes such a model, wherein solar irradiance is predicted, and nodes with less computational requirements are put to sleep. The model uses Exponentially Weighted Moving Average (EWMA) for estimation of a smarting factor as indicated by equation 2,

$$S = r * \left(\frac{C(t) - C(t-1)}{C(t) + C(t-1)}\right) * C(t) \ldots (2)$$

Where, r, C represents scaling constant, and energy observations at different time instances. Based on this factor, energy prediction is performed using equation 3 as follows,

$$E(t+1) = \big(a * E(t) + (1-a) * E(t-1)\big) * (1+L) * S \ldots (3)$$

Where, $a, E, and\ L$ represent prediction scaling constant, energy observation, and length of prediction interval respectively. The proposed model iPro-energy is able to achieve an efficiency of 81%, which is higher than Q-Learning Based Solar Energy Prediction (QLSEP) that has an accuracy of 75%, iPro that has an accuracy of 65%, and LPro that has an accuracy of 62% on the same network. Thereby making the proposed algorithm usable for real time deployments. A combination of these protocols along with cooperation-based scheduling can be observed from [4], wherein energy harvesting and energy transfer for transmission of data, with power control, scheduling & routing (EDPR) is proposed. The model utilizes Lyapunov optimization along with drift-plus-penalty & perturbation method for optimization. The model utilizes power as a data stream in order to cooperatively charge neighbouring nodes as observed from figure 2, wherein energy connections between nodes are observed. Due to the cooperative process, proposed model is able to achieve an energy efficiency of 85%, which is very high and suitable for real time network deployments with high lifetime.

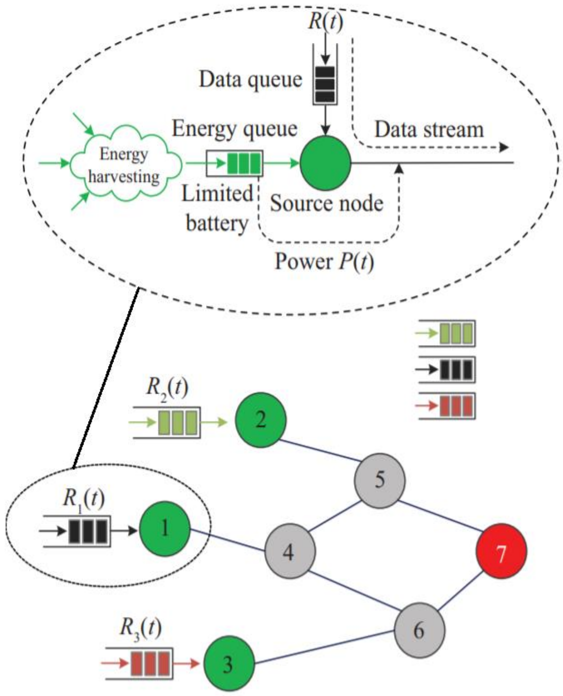


Figure 2. Cooperative energy harvesting in WSN [4]

This performance can be further improved via use of forecasting models as suggested in [3], but forecasting models have their own nuances, advantages, and limitations. The work in [5] highlights these characteristics and propose that neural network (NN) based hybrid methods like back propagation NN (BPNN) that has an energy efficiency of 65%, radial basis kernel feed forward network (RBFFN) that has an energy efficiency of 68%, Genetic Algorithm with NN (GANN) that has an energy efficiency of 71% and fuzzy ANN that has an energy efficiency of 67% models have better performance than other models like Extreme Learning Machine (ELM), and fuzzy approaches. The performance of these models is moderate due to use of a single renewable source, which can be improved using radio frequency (RF), thermal, wind flow, water flow, biomass, parametric changes in pressure, stress strain, vibration, & waste heat, body movements, body temperature, physiological parameters, electromagnetic (EM) waves, and hybrid sources. From this review it is observed that PV systems have an energy efficiency of 80%, RF energy harvesting have an energy efficiency of 64%, flow-based EHs have an energy efficiency of 53%, bio-energy models have an energy efficiency of 63%, thermal models have an energy efficiency of 86%, while mechanical systems have an efficiency of 6%, which indicates that bio-energy models & PV models must be combined for better EH systems.

An optimal size & rate (OSR) scheme that uses packet size, data rate, and maximum number of transmission trials (MNTT), are used for improving throughput & energy efficiency is proposed in [7], wherein periodic energy harvesting is proposed. The model showcases an energy efficiency of around 85% with a throughput of 7 kbps across different scenarios, which makes it useful for high performance WSN design. This efficiency can be improved using a modified single material energy harvesting device, which uses KNBNNO ceramic material as proposed in [8]. The proposed material is able to harvest solar, thermal, and kinetic changes via incorporation of photovoltaic, piezoelectric, and pyroelectric sensors. Circuit of the proposed model is showcased in figure 3, wherein pyro, photovoltaic, and piezo sensors are seen.

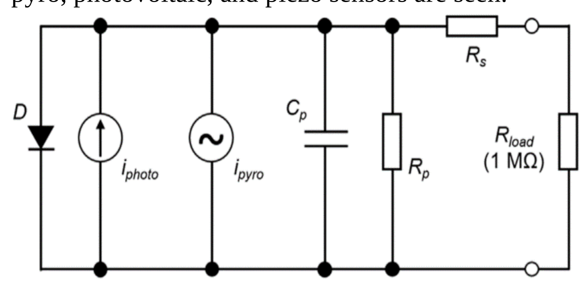


Figure 3. Proposed KNBNNO circuit design for energy harvesting [8]

The proposed model is observed to have an energy efficiency of 89%, which makes it suitable for real time deployments. But the cost of designing this model is very high, which can be resolved using mass production of the components. The proposed model's performance can be extended when combined with [9], wherein opportunistic routing protocol is proposed for EH WSN. The model utilizes long-short-term-memory (LSTM) to solve the energy sensing and consumption imbalance during solar power conversion. It also uses energy aware opportunistic routing (EAOR) for low power communications. The proposed model is observed to have an efficiency of 76%, and high QoS when compared to non-opportunistic routing scenarios. This efficiency can be extended using the work in [10], wherein resource allocation model using differential game theory is proposed. The model adaptively modifies speed, and power requirements during data communication based on traffic load & energy availability as observed from figure 4, wherein a neighbouring set is formed, depending upon energy harvesting & data sensing events.

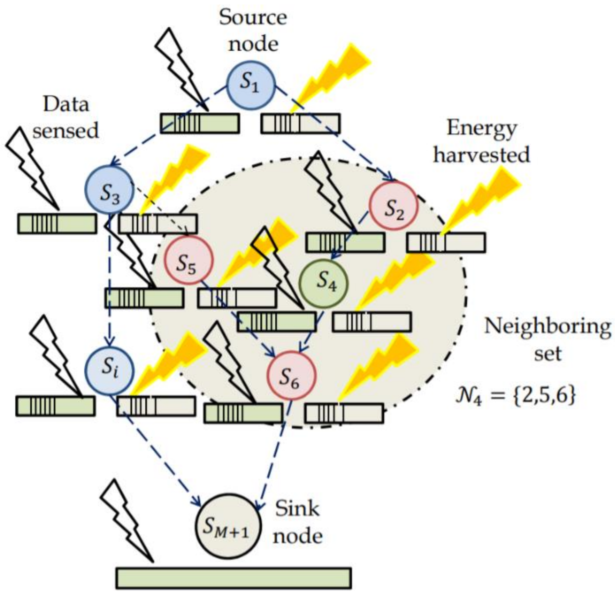


Figure 4. Event-based energy harvesting [10]

The model further uses receding-horizon-control with dynamic Game (RHCDG), for provision of reliable controllers to nonlinear sensing systems with constraints. The model is observed to have an energy efficiency of 80%, which makes it favourable for real time deployments, but the model is very computationally complex to implement, which limits its usability to high performance applications. This complexity can be extensively utilized by adding a greater number of sources for energy harvesting. For instance, the work in [11] can be referred where RF energy harvesting techniques are compared. It is observed that singe band designs have an energy efficiency of 62%, dual band & triple designs have an energy efficiency of 40%, while quad band designs have an efficiency of 84%, thereby facilitating the use of quad band designs for real time WSN node design. This efficiency can be extended with proper battery size design, which can limit number of update messages sent in the network. To facilitate this, the work in [12] can be used, wherein it is observed that optimum battery size depends upon number of nodes in the network. The work utilizes a queueing system as indicated in figure 5, wherein sensor nodes are observed to communicate their battery status signals on first come first serve (FCFS) basis.

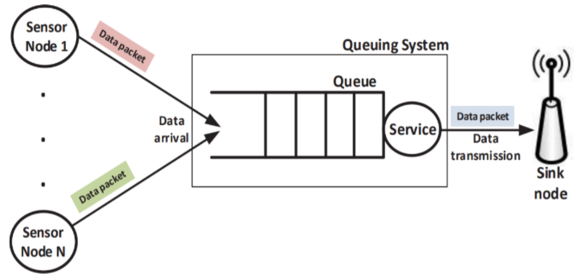


Figure 5. Use of FCFS for queuing battery signals [12]

Due to this, the proposed model is capable of obtaining an energy efficiency of 72% which makes it usable for large sized networks with optimum battery sizing. This framework can be extended by using the work in [13], wherein ordered transmissions scheme (OTS) based on Gaussian statistics. The proposed model is capable for improving energy efficiency to nearly 85%, by minimizing packet loss, and improving sensing interval hit ratio. Similar enhancement models are proposed in [14, 15], wherein fair cooperative protocol (FCP), and relay selection protocol (RSP) is used. These protocols have an energy efficiency of 65%, and 68% respectively. This efficiency can be optimized via use of improved cooperative routing scheme as proposed in [16], wherein underwater WSNs are used. The model uses a combination of cable connected, acoustic connected, and moored sensors in order to improve energy harvesting efficiency. The model works by bifurcating source load to different intermediaries, which are selected based on their residual energy, and distance metrics. Each node is given a harvesting trust value, which is calculated using equation 4 as follows,

$$EHT = \frac{Node\ to\ node\ distance}{Source\ residual\ energy} \ldots (4)$$

Nodes with low value of EHT are selected for communication, which results in minimum distance and maximum residual energy utilization. Number of data packets communicated through a node are selected using the following equation 5, wherein node residual energy is used a primary metric for controlling number of communicated packets (NCP).

$$NCP_i = Total\ Packets * \frac{Energy\ of\ i^{th}\ node}{Total\ energy\ of\ all\ selected\ nodes} \ldots (5)$$

Due to this energy-based packet distribution, the proposed model Cooperative Underwater WSN (Co-WSN) is able to achieve an energy efficiency of 83%, which is higher than normal EH-WSN that has an energy efficiency of 75% under the same network conditions. This performance can be improved via use of Energy-harvesting wastage-aware (EHWA), Sleep-wake scheduling and power control algorithm (SSPCA), Power splitting optimization (PoSO), Solar energy-prediction with Q-learning (QLSEP), Novel energy efficient clustering (NEEC), and clustering algorithm for energy efficiency (CAEE), as reviewed in [17]. It can be observed that NEEC has an energy efficiency of 57%, CAEE has an energy efficiency of 55%, QLSEP has an energy efficiency of 68%, PoSO has an energy efficiency of 65%, SSPCA has an energy efficiency of 71%, and EHWA has an energy efficiency of 80%, thereby suggesting that EHWA should be applied to real time EH WSNs.

A similar, highly efficient algorithm for energy optimization can be observed from [18], wherein distributed optimization based on potential game theoretic approach is defined. The model is based on prediction of power consumption over 2 days and using this predicted data for allocating routing and computation load to nodes. An energy efficiency of 83% is achieved using this model, which makes it highly usable for real time networks. Similar models are proposed in [19, 20, 21, 22] wherein inverter based photovoltaic circuit design (IBPVCD) that achieves 79% efficiency, Markovian model with modified opportunistic routing (MEHOR) that achieves 90% efficiency, EHOR that achieves 85% efficiency, collar mounted device design (CMDD) that achieves 76% efficiency and update internal violation probability (UIVP) based energy harvesting that achieves 74% energy efficiency are proposed. These models are used for high performance network design, and can be deployed for low cost, and low power networks.

During design of these networks, a wide variety of censoring rules are applied, the work in [23] highlights these rules, and indicates that battery sizing, mobility limits, and mean squared error (MSE) bounds must be kept in check while designing battery powered WSN nodes. Based on these conditions, work in [24, 25, 26, 27] proposes design of maximum power point transfer with PV (MPPT PV) with energy efficiency of 96%, RF harvesting at the header of timeslot (RF HHT) with energy efficiency of 72%, RF harvesting at the dedicated timeslot (RF HDT) with energy efficiency of 79%, particle swarm optimization (PSO) for cooperative communication (PSO CC) with an energy efficiency of 63%, and adaptive medium access control (AMAC) for PV harvesting (AMAC PV) with an energy efficiency of 85% are seen. These models have better QoS, and are used for moderately sized WSNs, that have moderate processing power. Similar models are reviewed in [28, 29, 30], wherein it is observed that machine learning models that utilize deep learning have limited use in energy harvesting, while rule-based systems are more suited towards providing high energy efficiency in EH WSNs.

Applications of these models are observed from [31, 32], wherein river monitoring, and evaluation of connectivity performance, are proposed. The performance of these applications can be improved via use of cooperative reinforcement learning (CRL) as proposed in [33], wherein throughput is optimized via idle time, sensing time, computing time, and transmission time optimization. The model showcases an energy efficiency of 79% but has high computation complexity due to implementation of RL model. This complexity can be reduced via use of feature selection for energy sources, which assists in identification of best harvesting source for the given environmental conditions. It is observed that the proposed model [34] is able to achieve an energy efficiency of 85%, but is expensive in terms of deployment, due to a large number of sensing devices. This cost can be reduced via use of optimal number of sensing devices, which are identified to have highest efficiency. The selection process is further facilitated using mixed integer nonlinear programming optimization (MINLPO), and optimal sink speed allocation (OSSAA) proposed in [35] that achieves an energy efficiency of 71%, which is higher than adjustment led allocation (ALA) that has an efficiency of 68% under the same network conditions. Similar models are proposed in [36, 37, 38] wherein path planning (PP), Uniform Random Ordered Policy (UROP), Myopic Policy (MP), and path exposure (EXPO), which achieve an energy efficiency of 54%, 65%, 68%, and 85% respectively. This efficiency can be further improved via enhanced clustering mechanisms like, Energy Harvesting Cluster Head Rotation Scheme (EH-CHRS) [39], and Solar Energy-Harvesting with Improved Cluster Head Selection (SEH-ICHS) [40], wherein an energy efficiency of 89% and 91% are achieved. This efficiency is higher when compared with Low-energy adaptive clustering hierarchy (LEACH) that has an energy efficiency of 85%, and distributed energy efficient clustering (DEEC) that has an energy efficiency of 79%, thereby making SEH-ICHS most suitable choice for a wide variety of network scenarios. Based on this review, it is observed that a wide variety of models are defined for energy harvesting in wireless networks, Statistical analysis of these models, which will assist in identification of the best method for a given network scenario can be observed from the next section.

STATISTICAL ANALYSIS

Evaluation of efficiency for energy harvesting models in WSNs requires comparison of the proposed models on different statistical parameters. These parameters include, energy efficiency (EE), computational complexity (CC), cost of deployment (CD), and application type (AT). These parameters are estimated from the reviewed models, and tabulated in table 1, wherein computational complexity and cost of deployment are converted into fuzzy ranges of low (L), medium (M), high (H), and very high (VH) depending upon their relative values.

Method	CC	CD	EE	AT
NEHCP [2]	M	M	71	General
SEED [2]	H	M	61.8	General
HUCL [2]	H	M	45.7	General
CEEC [2]	M	L	37.7	General
iPro EWMA [3]	H	M	81	PV
QLSEP [4]	H	H	75	PV
iPro [4]	H	M	65	PV
LPro [3]	M	M	62	PV
EDPR [4]	M	H	85	PV
BPNN [5]	H	H	65	General
RBFFN [5]	H	H	68	General
GANN [5]	M	M	71	General
Fuzzy ANN [5]	H	M	67	General
MPPT PV [6]	M	M	80	PV
MPPT RF [6]	M	M	64	RF
MPPT Flow [6]	M	M	53	Mech.
MPPT Bio [6]	M	M	63	Mech.
MPPT Thermal [6]	M	M	86	Thermal
OSR [7]	M	M	85	General
KNBNNO [8]	M	H	89	General
EAOR LSTM [9]	VH	H	76	PV
RHCDG [10]	H	VH	80	General
Single band RF [11]	M	M	62	RF
Dual band RF [11]	M	M	40	RF
Triple band RF [11]	M	H	40	RF
Quad Band RF [11]	M	H	84	RF
Queue FCFS [12]	M	H	72	General
OTS [13]	H	H	85	General
FCP [14]	M	H	65	General
RSP [15]	M	H	68	General
Co-WSN [16]	H	H	83	Mech.
EH-WSN [16]	M	M	75	Mech.
NEEC [17]	M	L	57	General
CAEE [17]	M	M	55	General
QLSEP [17]	M	H	68	General
PoSO [17]	M	M	65	General
EHWA [17]	M	H	80	General
SSPCA [17]	M	H	71	General
Game theory [18]	H	H	83	General
IBPVCD [19]	H	H	79	PV
MEHOR [20]	H	H	90	General
EHOR [20]	H	H	85	General
CMDD [21]	M	H	76	Mech.
UIVP [22]	M	M	74	General
MPPT PV [24]	M	M	96	PV
RF HHT [25]	M	M	72	RF
RF HDT [25]	M	H	79	RF
PSO CC [26]	H	H	63	General
AMAC PV [27]	H	M	85	PV
CRL [33]	H	H	79	General
Feature selection [34]	H	H	85	General
MINLPO with OSSAA [35]	H	H	71	General
ALA [35]	M	H	68	General
PP [36]	M	M	54	General
UROP [37]	H	M	65	General
EXPO [38]	H	H	68	General
EH-CHRS [39]	H	H	89	General
SEH-ICHS [40]	H	H	91	PV

Table 1. Statistical evaluation of reviewed models *(Mech.: Mechanical)*

These statistical comparisons are further bifurcated into General purpose, PV, RF and mechanical types. General purpose types include are applicable for all energy sources, while PV, RF, and mechanical types are applicable for solar, RF and piezo-electric powered applications. Based on this bifurcation, energy efficiency of different mechanical based EH WSNs can be observed from figure 6 as follows,

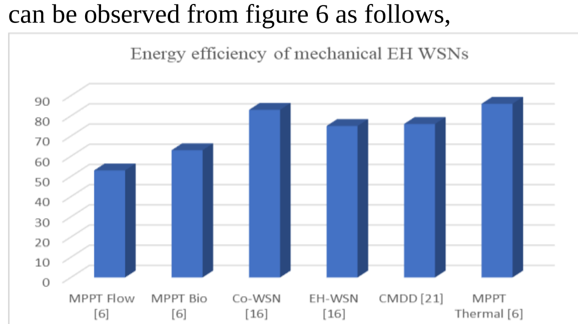


Figure 6. Energy efficiency of mechanical EH WSN systems

Based on this comparison, it is observed that MPPT Thermal [6], Co-WSN [16], CMDD [21], and EH-WSN [16] are the most effective models in terms of energy efficiency for mechanical EH systems. Similarly, computational complexity of different mechanical based EH WSNs can be observed from figure 7 as follows,

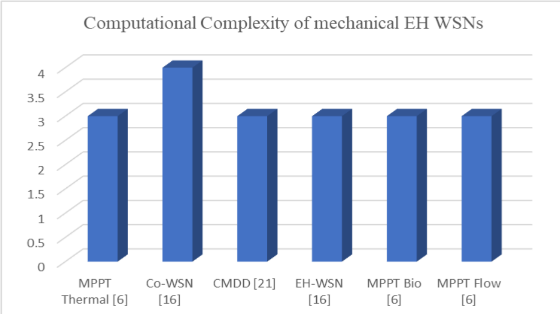


Figure 7. Computational complexity of mechanical EH WSN systems

Based on this comparison, it is observed that MPPT Thermal [6], CMDD [21], EH-WSN [16], and MPPT Bio [6] are the most effective models in terms of computational complexity for mechanical EH systems. Similarly, cost of deployment for different mechanical based EH WSNs can be observed from figure 8 as follows,

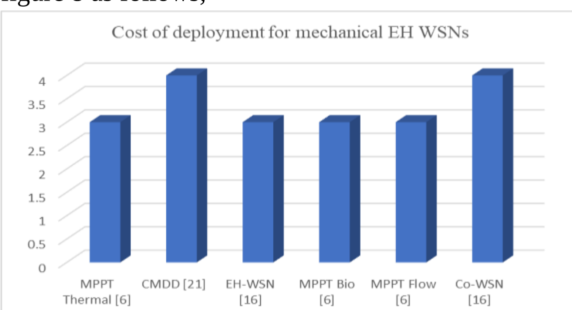


Figure 8. Cost of deployment for mechanical EH WSN systems

Based on this comparison, it is observed that MPPT Thermal [6], CMDD [21], EH-WSN [16], and MPPT Bio [6] are the most effective models in terms of computational complexity for mechanical EH systems.

The energy efficiency of different RF based EH WSNs can be observed from figure 9 as follows,

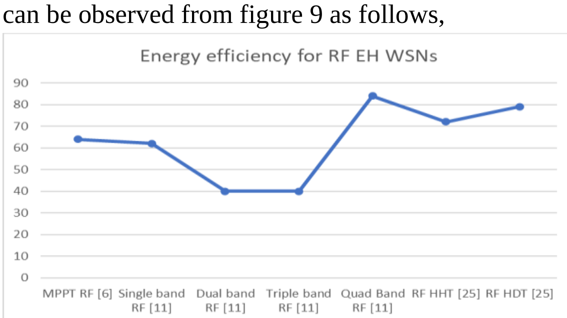


Figure 9. Energy efficiency of RF EH WSN systems

Based on this comparison, it is observed that Quad Band RF [11], RF HDT [25], RF HHT [25], MPPT RF [6] and Single band RF [11] are the most effective models in terms of energy efficiency for RF EH systems. Similarly, computational complexity of different RF based EH WSNs can be observed from figure 10 as follows,

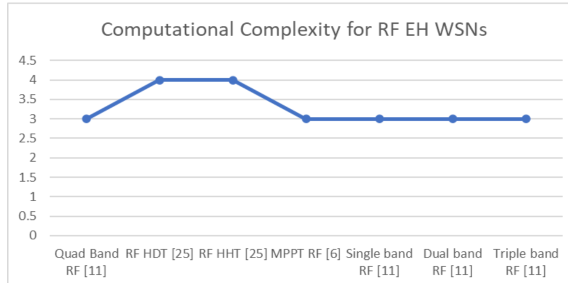


Figure 10. Computational complexity of RF EH WSN systems

Based on this comparison, it is observed that Quad Band RF [11], MPPT RF [6], Single band RF [11], Dual band RF [11], and Triple band RF [11] are the most effective models in terms of computational complexity for RF EH systems. Similarly, cost of deployment for different RF based EH WSNs can be observed from figure 11 as follows,

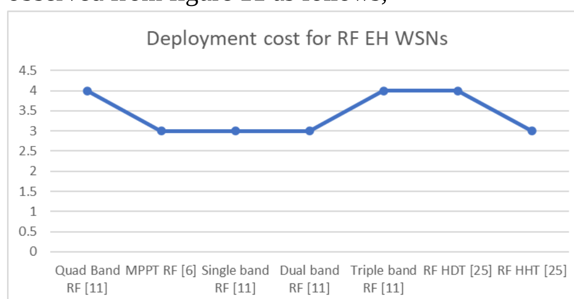


Figure 11. Cost of deployment for RF EH WSN systems

Based on this comparison, it is observed that MPPT RF [6], Single band RF [11], Dual band RF [11], and RF HHT [25] are the most effective models in terms of deployment cost for RF EH systems.

The energy efficiency of different PV based EH WSNs can be observed from figure 12 as follows,

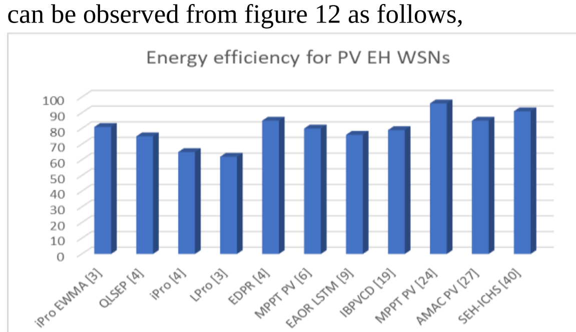


Figure 12. Energy efficiency of PV EH WSN systems

Based on this comparison, it is observed that MPPT PV [24], SEH-ICHS [40], EDPR [4], AMAC PV [27], iPro EWMA [3], and MPPT PV [6] are the most effective models in terms of energy efficiency for PV EH systems. Similarly, computational complexity of different PV based EH WSNs can be observed from figure 13 as follows,

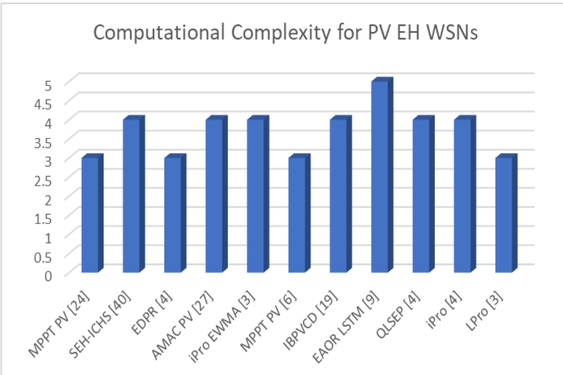


Figure 13. Computational complexity of PV EH WSN systems

Based on this comparison, it is observed that MPPT PV [24], EDPR [4], MPPT PV [6], LPro [3], SEH-ICHS [40], and AMAC PV [27] are the most effective models in terms of computational complexity for PV EH systems. Similarly, cost of deployment for different PV based EH WSNs can be observed from figure 14 as follows,

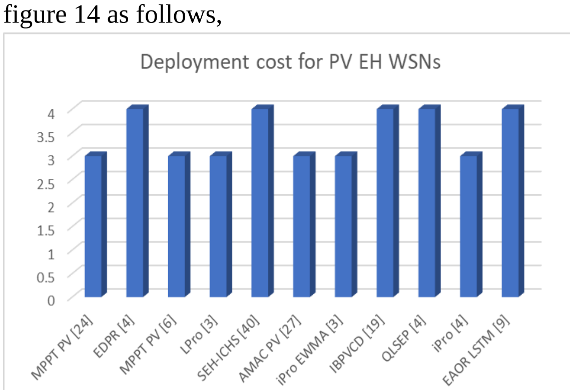


Figure 14. Cost of deployment for PV EH WSN systems

Based on this comparison, it is observed that MPPT PV [24], MPPT PV [6], LPro [3], AMAC PV [27], iPro EWMA [3], and iPro [4] are the most effective models in terms of deployment cost for PV EH systems.

The energy efficiency, computational complexity, and cost of deployment for different General purpose EH WSNs can be observed from figure 15 as follows,

Figure 15. Energy efficiency of General purpose EH WSN systems

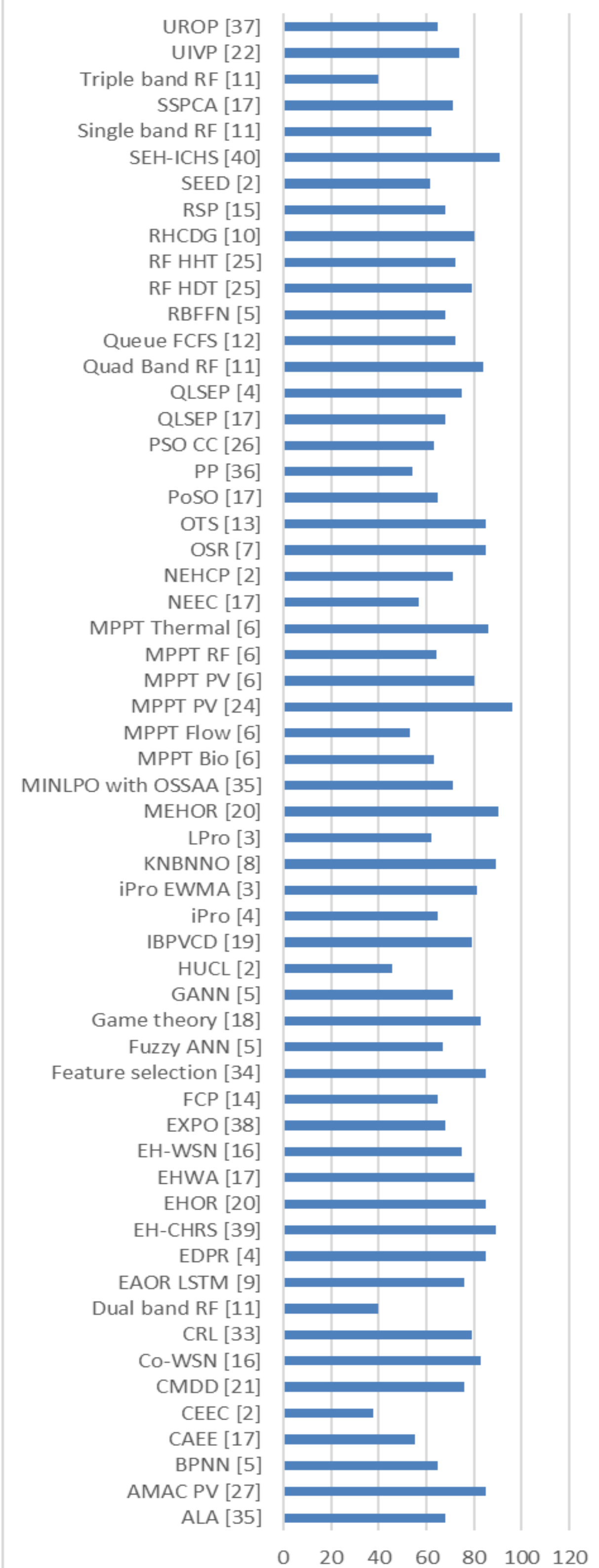


Figure 16. CC of General purpose EH WSN systems

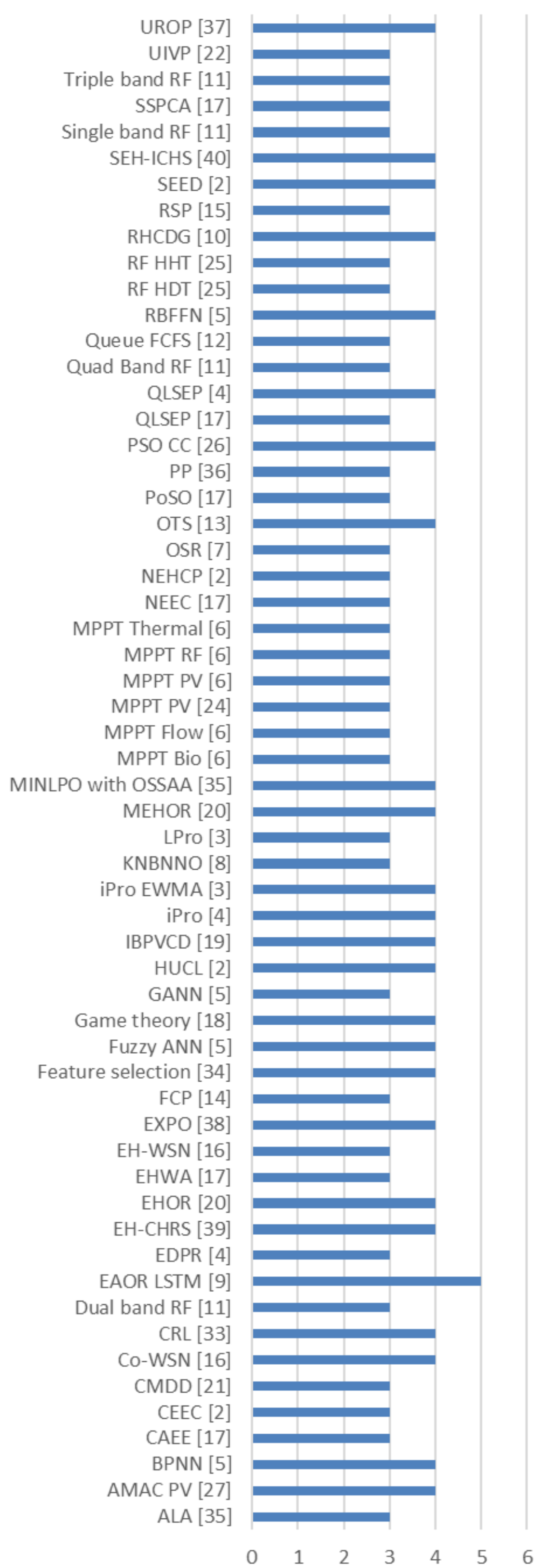
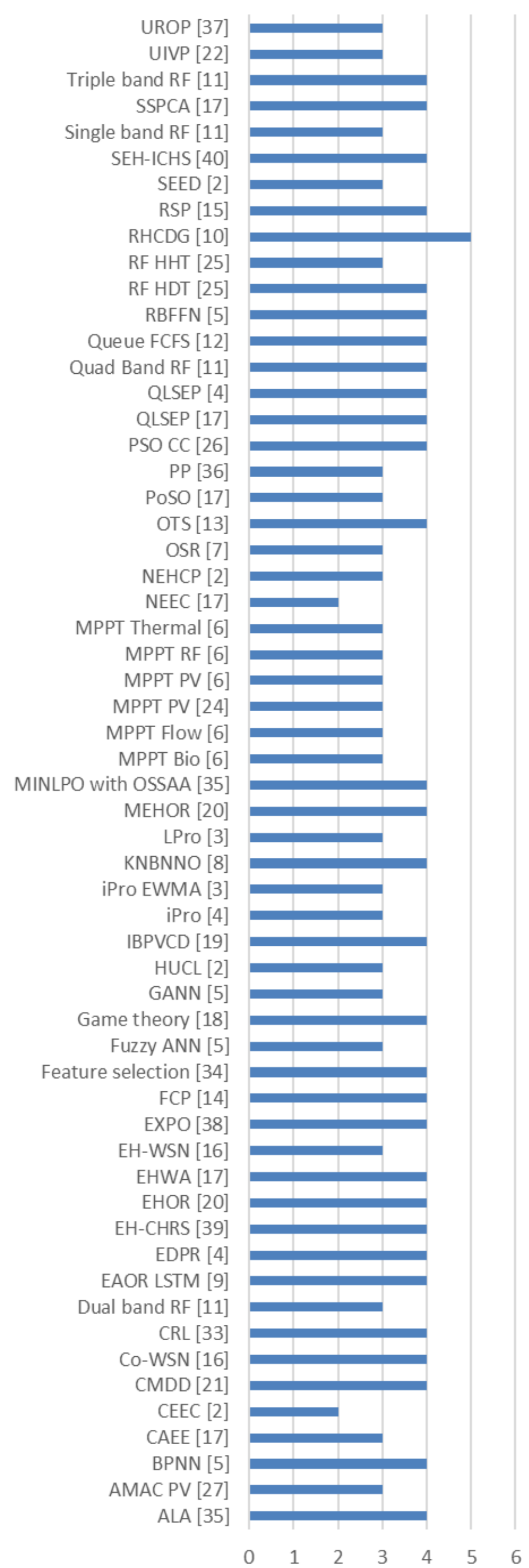


Figure 17. CD for General purpose EH WSN systems



Based on this comparison, it is observed that MPPT PV [24], SEH-ICHS [40], MEHOR [20], KNBNNO [8], EH-CHRS [39], MPPT Thermal [6], OSR [7], OTS [13], EHOR [20], Feature selection [34], EDPR [4], AMAC PV [27], Quad Band RF [11], Game theory [18], Co-WSN [16], and iPro EWMA [3] are the most effective models in terms of energy efficiency for General purpose EH systems. Further, it is observed that MPPT PV [24], KNBNNO [8], MPPT Thermal [6], OSR [7], EDPR [4], Quad Band RF [11], EHWA [17], MPPT PV [6], RF HDT [25], CMDD [21], EH-WSN [16], UIVP [22], Queue FCFS [12], RF HHT [25], NEHCP [2], GANN [5], SSPCA [17], RSP [15], and QLSEP [17] are the most effective models in terms of computational complexity for General purpose EH systems. Finally, it is observed that NEEC [17], CEEC [2], MPPT PV [24], MPPT Thermal [6], OSR [7], MPPT PV [6], EH-WSN [16], UIVP [22], RF HHT [25], NEHCP [2], GANN [5], PoSO [17], MPPT RF [6], MPPT Bio [6], LPro [3], Single band RF [11], CAEE [17], PP [36], and MPPT Flow [6] are the most effective models in terms of deployment cost for General purpose EH systems. Using these observations, researchers and WSN system designers can select the best suited models for their application deployments.

CONCLUSION AND FUTURE WORK

The extensive review based on different parameters of EH based WSN models suggests that MPPT Thermal [6], and Co-WSN [16], are the most effective models in terms of energy efficiency, MPPT Thermal [6], and CMDD [21] are the most effective models in terms of computational complexity, while MPPT Thermal [6], and CMDD [21] are the most effective models in terms of computational complexity for mechanical EH systems. Thus, MPPT Thermal and CMDD can be selected as EH models when designing mechanical power based WSN systems. Similarly, it is observed that Quad Band RF [11], and RF HDT [25] are the most effective models in terms of energy efficiency, Quad Band RF [11], and MPPT RF [6] are the most effective models in terms of computational complexity, and MPPT RF [6], Single band RF [11], and Dual band RF [11] are the most effective models in terms of deployment cost for RF EH systems. Based on similar observations, it is perceived that MPPT PV [24], SEH-ICHS [40], EDPR [4], and AMAC PV [27] are the most effective models in terms of energy efficiency, MPPT PV [24], EDPR [4], LPro [3], SEH-ICHS [40], and AMAC PV [27] are the most effective models in terms of computational complexity, and MPPT PV [24], LPro [3], AMAC PV [27], and iPro EWMA [3] are the most effective models in terms of deployment cost for PV EH systems.

Finally, it is observed that MPPT PV [24], SEH-ICHS [40], MEHOR [20], and KNBNNO [8] are the most effective models in terms of energy efficiency, MPPT PV [24], KNBNNO [8], MPPT Thermal [6], and OSR [7] are the most effective models in terms of computational complexity, NEEC [17], CEEC [2], MPPT PV [24], and MPPT Thermal [6] are the most effective models in terms of deployment cost for General purpose EH systems. Using these observations, researchers and WSN system designers can select the best suited models for their application deployments. Further, it is recommended that researchers must perform combinatorial evaluation of these models, and interface mechanical models with PV models, PV models with RF models, and RF models with General purpose models, in order to design hybrid EH systems. This must be done by keeping the cost of deployment & computational complexity as low as possible, while keeping energy efficiency as high as possible. Researchers can design Genetic Algorithms (GAs) or other bio-inspired models in order to perform this task.

REFERENCES

[1] Fahmy H. (2020) Wireless Sensor Networks Essentials. In: Wireless Sensor Networks. Signals and Communication Technology. Springer, Cham. https://doi.org/10.1007/978-3-030-29700-8_1

[2] Sah, D.K., Amgoth, T. A novel efficient clustering protocol for energy harvesting in wireless sensor networks. Wireless Netw 26, 4723–4737 (2020). https://doi.org/10.1007/s11276-020-02351-x

[3] Deb, M., Roy, S. Enhanced-Pro: A New Enhanced Solar Energy Harvested Prediction Model for Wireless Sensor Networks. Wireless Pers Commun 117, 1103–1121 (2021). https://doi.org/10.1007/s11277-020-07913-y

[4] Zhu, P., Xu, B., Li, J. et al. Joint utility optimization for wireless sensor networks with

energy harvesting and cooperation. Sci. China Inf. Sci. 63, 122302 (2020). https://doi.org /10.1007/s11432-019-9936-y

[5] Sharma, A, kakkar, A. A review on solar forecasting and power management approaches for energy harvesting–wireless sensor networks. Int J Commun Syst. 2020; 33:e4366. https://doi.org/10.1002/dac.4366

[6] Singh, J, Kaur, R, Singh, D. Energy harvesting in wireless sensor networks: A taxonomic survey. Int J Energy Res. 2021; 45: 118– 140. https://doi.org/10.1002/er.5816

[7] Bai, N., Gong, S., Shi, H., Cheng, Z. and Zhu, Y. (2019), Improving Throughput of Communication Link in IEEE 802.15.4 Based Energy-Harvesting Wireless Sensor Network. Chinese J. Electron., 28: 841-849. https://doi.org/10.1049/cje.2019.03.003

[8] Bai, Y., Palosaari, J., Tofel, P. and Juuti, J. (2020), A Single-Material Multi-Source Energy Harvester, Multifunctional Sensor, and Integrated Harvester–Sensor System—Demonstration of Concept. Energy Technol., 8: 2000461. https://doi.org/10.1002/ente.202000461

[9] Y. Li, X. He and C. Yin, "Energy Aware Opportunistic Routing for Energy Harvesting Wireless Sensor Networks," 2020 IEEE 31st Annual International Symposium on Personal, Indoor and Mobile Radio Communications, 2020, pp. 1-6, doi: 10.1109/PIMRC 48278. 2020. 9217148.

[10] H. Al-Tous and I. Barhumi, "Differential Game for Resource Allocation in Energy Harvesting Sensor Networks," 2018 IEEE International Conference on Communications (ICC), 2018, pp. 1-6, doi: 10.1109/ICC.2018.8422091.

[11] M. Sansoy, A. S. Buttar and R. Goyal, "Empowering Wireless Sensor Networks with RF Energy Harvesting," 2020 7th International Conference on Signal Processing and Integrated Networks (SPIN), 2020, pp. 273-277, doi: 10.1109/SPIN48934.2020.9071376.

[12] A. Hentati, W. Jaafar, J. Frigon and W. Ajib, "Update Interval Violation Probability in Energy Harvesting Wireless Sensor Networks," 2020 IEEE 17th Annual Consumer Communications & Networking Conference (CCNC), 2020, pp. 1-6, doi: 10.1109/CCNC46108.2020.9045626.

[13] S. Sen Gupta, S. K. Pallapothu and N. B. Mehta, "Ordered Transmissions for Energy-Efficient Detection in Energy Harvesting Wireless Sensor Networks," in IEEE Transactions on Communications, vol. 68, no. 4, pp. 2525-2537, April 2020, doi: 10.1109/TCOMM. 2020. 2964545.

[14] Z. Mheich and V. Savin, "Cooperative communication protocols with energy harvesting relays," 2017 Wireless Days, 2017, pp. 60-65, doi: 10.1109/WD.2017.7918116.

[15] Jianrong Bao, Jiawen Wu, Chao Liu, Bin Jiang, Xianghong Tang, "Optimized Power Allocation and Relay Location Selection in Cooperative Relay Networks", Wireless Communications and Mobile Computing, vol. 2017, Article ID 9727360, 10 pages, 2017. https://doi.org/10.1155/2017/9727360

[16] Sheeraz Ahmed, Malik Taimur Ali, Asma A. Alothman, Asif Nawaz, M. Shahzad, Ahmed Ali Shah, Awais Ahmad, M. Yousaf Ali Khan, Zeeshan Najam, Asma Shaheen, "EH-UWSN: Improved Cooperative Routing Scheme for UWSNs Using Energy Harvesting", Journal of Sensors, vol. 2020, Article ID 8888957, 18 pages, 2020. https://doi.org/10.1155/2020/8888957

[17] Sharma, Vinod & Mukherji, U. & Joseph, V. (2012). Algorithms for Energy-Harvesting wireless networks. Green Radio Communication Networks.24-52.10.1017/CBO9781139084284. 003.

[18] Lingfeng Shao, Junjie Yang, Jicheng Fang, "A Distributed Optimization Algorithm for Energy of Wireless Sensor Networks Based on Potential Game", International Journal of Photoenergy, vol. 2020, Article ID 4745678, 11 pages, 2020. https://doi.org/10.1155/2020/4745678

[19] H. Sharma, A. Haque and Z. A. Jaffery, "An Efficient Solar Energy Harvesting System for Wireless Sensor Nodes," 2018 2nd IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), 2018, pp. 461-464, doi: 10.1109/ICPEICES.2018.8897434.

[20] Debabrata Singh & Binod Kumar Pattanayak (2020) Markovian model analysis for energy harvesting nodes in a modified opportunistic routing protocol, International Journal of

Electronics, 107:12, 1963-1984, DOI: 10.1080/00207217.2020.1756444

[21] Adu-Manu, Kofi & Adam, Nadir & Tapparello, Cristiano & Ayatollahi, Hoda & Heinzelman, Wendi. (2018). Energy-harvesting wireless sensor networks (EH-WSNs): A review. ACM Transactions on Sensor Networks. 14. 1-50. 10.1145/3183338.

[22] Fahmy H. (2020) Energy Harvesting Projects for WSNs. In: Wireless Sensor Networks. Signals and Communication Technology. Springer, Cham. https://doi.org/10.1007/978-3-030-29700-8_7

[23] S. Sen Gupta and N. B. Mehta, "Revisiting Censoring in Energy Harvesting Wireless Sensor Networks," 2018 IEEE Global Communications Conference (GLOBECOM), 2018, pp. 1-6, doi: 10.1109/GLOCOM.2018.8647464.

[24] H. Sharma, A. Haque and Z. A. Jaffery, "An Efficient Solar Energy Harvesting System for Wireless Sensor Nodes," 2018 2nd IEEE International Conference on Power Electronics, Intelligent Control and Energy Systems (ICPEICES), 2018, pp. 461-464, doi: 10.1109/ICPEICES.2018.8897434.

[25] Tran, H., Åkerberg, J., Björkman, M. et al. RF energy harvesting: an analysis of wireless sensor networks for reliable communication. Wireless Netw 25, 185–199 (2019). https://doi.org/10.1007/s11276-017-1546-6

[26] Nikita N Bharadwaj, Jaya Dipti Lal, S.V. Charhate. Optimal power allocation using particle swarm optimization in cooperative wireless sensor networks, International Journal of Advance Research, Ideas and Innovations in Technology, www.IJARIIT.com.

[27] Kaur, Pardeep & Singh, Preeti. (2020). Adaptive MAC Protocol for Solar Energy Harvesting Based Wireless Sensor Networks in Agriculture. Wireless Personal Communications. 10.1007/s11277-019-06985-9.

[28] López-Ardao JC, Rodríguez-Rubio RF, Suárez-González A, Rodríguez-Pérez M, Sousa-Vieira ME. Current Trends on Green Wireless Sensor Networks. Sensors. 2021; 21(13):4281. https://doi.org/10.3390/s21134281

[29] Alsharif MH, Kim S, Kuruoğlu N. Energy Harvesting Techniques for Wireless Sensor Networks/Radio-Frequency Identification: A Review. Symmetry. 2019; 11(7):865. https://doi.org/10.3390/sym11070865

[30] Mile Stojcev, Zoran Stamenkovic, Bojan Dimitrijevic, "Energy Conservation and Harvesting in Wireless Sensor Networks", Wireless Communications and Mobile Computing, vol. 2019, Article ID 7640232, 2 pages, 2019. https://doi.org/10.1155/2019/7640232

[31] Kofi Sarpong Adu-Manu, Ferdinand Apietu Katsriku, Jamal-Deen Abdulai, Felicia Engmann, "Smart River Monitoring Using Wireless Sensor Networks", Wireless Communications and Mobile Computing, vol. 2020, Article ID 8897126, 19 pages, 2020. https://doi.org/10.1155/2020/8897126

[32] H. Cong, Q. Li, C. Zhou and Q. Yang, "Analysis on Connectivity of Energy Harvesting Wireless Sensor Networks Based on Simulation," 2018 International Conference on Computing, Networking and Communications (ICNC), 2018, pp. 762-768, doi: 10.1109/ICCNC.2018.8390272.

[33] Y. Wu and K. Yang, "Cooperative reinforcement learning based throughput optimization in energy harvesting wireless sensor networks," 2018 27th Wireless and Optical Communication Conference (WOCC), 2018, pp. 1-6, doi: 10.1109/WOCC.2018.8372691.

[34] M. K. Lagha, F. A. Aoudia, M. Gautier and O. Berder, "Feature Selection Framework for Multi-Source Energy Harvesting Wireless Sensor Networks," 2018 IEEE 87th Vehicular Technology Conference (VTC Spring), 2018, pp. 1-5, doi: 10.1109/VTCSpring.2018.8417656.

[35] A. Mehrabi, "Optimal Speed Allocation in Sink-Based Energy Harvesting Wireless Sensor Networks," 2018 IEEE 32nd International Conference on Advanced Information Networking and Applications (AINA), 2018, pp. 128-134, doi: 10.1109/AINA.2018.00031.

[36] W. Liao, S. Kuai and C. Chang, "Energy Harvesting Path Planning Strategy on the Quality of Information for Wireless Sensor Networks," 2019 IEEE International Conference of Intelligent Applied Systems on Engineering (ICIASE), 2019, pp. 82-85, doi: 10.1109/ICIASE45644. 2019 .90 74030.

[37] O. M. Gul, "Achieving Near-Optimal Fairness in Energy Harvesting Wireless Sensor Networks,"

2019 IEEE Symposium on Computers and Communications (ISCC), 2019, pp. 1-6, doi: 10.1109/ISCC47284.2019.8969740.
[38] A. Basabaa and E. S. Elmallah, "Bounds on Path Exposure in Energy Harvesting Wireless Sensor Networks," 2019 IEEE Wireless Communications and Networking Conference (WCNC), 2019, pp. 1-7, doi: 10.1109/WCNC.2019.8886159.
[39] Mahima, V., Chitra, A. A Novel Energy Harvesting: Cluster Head Rotation Scheme (EH-CHRS) for Green Wireless Sensor Network (GWSN). Wireless Pers Commun 107, 813–827 (2019). https://doi.org/10.1007/s11277-019-06302-4
[40] Sharma, D., Bhondekar, A.P. An Improved Cluster Head Selection in Routing for Solar Energy-Harvesting Multi-heterogeneous Wireless Sensor Networks. Wireless Pers Commun 108, 2213–2228 (2019). https://doi.org/10.1007/s11277-019-06518-4