International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

LCEMILCP: Design of a Low-Complexity Energy Harvesting Model via Incremental Learning and Continuous Power Quality Optimization Process in wsn

Dr. (Mrs.) Jaya Dipti Lal

Associate Professor, Department of Electronics & Tc Department, Shri G.S. Institute of Technology & Science, Indore, India

Abstract:
Optimization of energy harvesting requires design of low complexity & high efficiency models that can work with maximum power gain levels. To design such models, researchers have proposed multiple techniques, that can assist in improving power quality via selection of optimum harvesting sources in multisource environments. But these models require continuous reconfiguration of static rules, which limits their efficiency when applied to large-scale network scenarios. Moreover, most of these models also showcase higher complexity due to reconfiguration, which reduces their scalability performance. To overcome this limitation, a novel Low-Complexity Energy Harvesting Model via Incremental Learning and Continuous Power Quality Optimization process is discussed in this text. The proposed model initially uses a Q-Learning based power evaluation method, that is capable of generating high-efficiency configurations of multisource harvesting devices. This is cascaded with design of a Particle Swarm Optimizer (PSO), that assists in performing continuous power quality optimizations. The combined model is capable of selecting hybrid harvesting source configurations, and incrementally tune it for optimum harvesting performance. This is achieved via modelling a reward function that incorporates power gain along with low-complexity source selection process. The selection process is further enhanced via PSO based continuous learning for improving harvesting source configurations. The proposed model was tested on a wide variety of network scenarios, and its QoS efficiency levels were compared with different state-of-the-art methods. Based on this comparison, it was observed that the proposed model is capable of improving power gain by 8.3%, while minimizing harvesting delay by 6.5%, and improving harvesting throughput by 5.9%, which makes it useful for large-scale multisource harvesting applications.

Keywords: Energy, Harvesting, Multisource, Throughput, Delay, Power, Gain, PSO, Q-Learning, Configurations

1. Introduction

Multisource energy harvesting requires integration of different signal processing & optimization operations, that can perform source selection along with low complexity source reconfigurations. These models use a combination of Maximum Power Point Tracking (MPPT) along with machine learning based optimization techniques, which assists in improving their power gain efficiency, while maximizing network lifetime under wide variety of use cases. A typical harvesting model [1] that uses machine learning based energy flow controller along with storage capacitors is depicted in figure 1, wherein energy adapters & DC-DC converters are used for power conversion operations. The model is used for Solar & Thermal energy types, but can be extended for other sources via minimum reconfiguration operations. Due to integration of machine learning for energy flow control, the model is capable of demonstrating higher energy conversion efficiency, via maximization of power generation performance levels. Its performance can be further optimized via use of hybrid machine learning models, which assist in multiobjective optimizations.

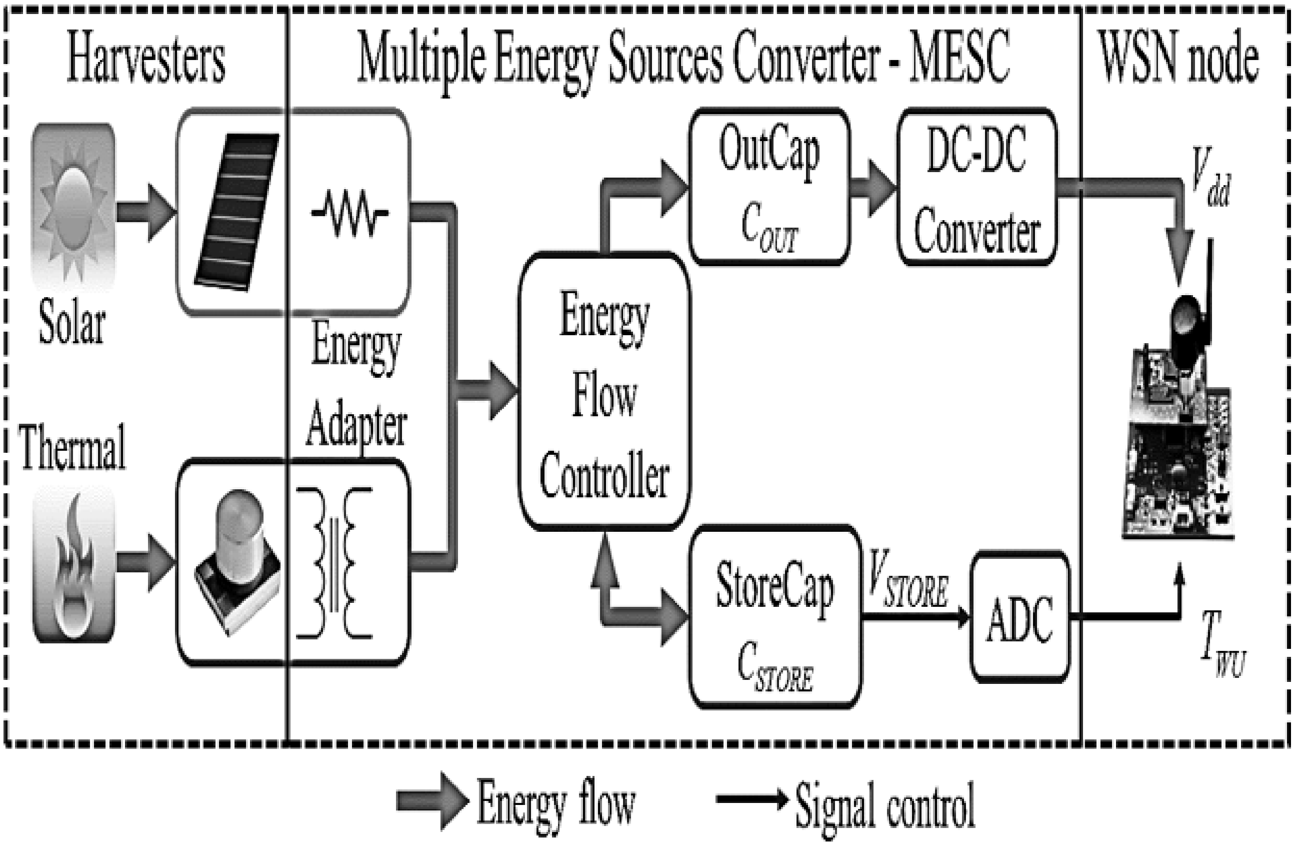

Figure 1. Design of a typical multisource harvesting model via energy flow control process

Such models [2, 3, 4] along with their source-specific nuances, application-specific advantages, contextual limitations, and deployment-specific future scopes are discussed in the next section of this text. Based on this discussion it was observed that existing models require continuous reconfiguration of static rules, which limits their efficiency when applied to large-scale network scenarios. Moreover, most of these models also showcase higher complexity due to reconfiguration, which reduces their scalability performance. To overcome this limitation, a novel Low-Complexity Energy Harvesting Model via Incremental Learning and Continuous Power Quality Optimization process is discussed in section 3 text. The model's performance was evaluated in terms of efficiency of power generation, throughput & delay, and compared with various state-of-the art methods in section 4, which assists in validating its efficiency under real-time use cases. Finally, this text is concluded with some contextual observations about the proposed model, and it also recommends various ways to further optimize its performance under different use cases.

2. Literature review

Alternative harvesting models for wireless devices have been created by researchers to improve their energy efficiency under various harvesting sources. Adaptive duty cycle harvesting with BECC and Energy-Neutral Operation, for example, are suggested in [5, 6] studies to maximize harvesting performance. This model's scalability is limited by the fact that it is designed for a single source harvesting application. Using MLMs that can accommodate nonlinear energy consumption, wake-up time, and power changes during continuous data transfers is recommended in [7] in order to improve this performance. The model was developed for use with RF sources, although it might also be used to other types of harvesting. Finite-state Markov energy channels (FSMEC), Maximum Power Point Tracking with Energy Storage, and Data and Energy Integrated Networks (DEIN) are some of the models investigated in [8, 9, 10], which advocate using these techniques to increase harvesting performance continuously. There are a number of ways to improve the efficiency of harvesting processes, including the use of Improved Uneven Clustering (IUC) [11], Linear Optimizations [12], cooperative integration modules (13), and Markov Decision Process (MDP) [14]. These models are ideal for low-power deployment and may be adapted to gather from several sources.

Distributed Coordination Function (DCF) [15], Modified Improved Opportunistic Ring Routing Protocol (MIORP) [16], Time-synchronized Channel Hoping (TSCH) [17], and the Hungarian Model (HM) [18] are examples of models that use large-scale network analysis metrics to help optimize harvester performance through the integration of harvesters. When it comes to harvesting process installations that are more efficient and less wasteful, they include location-based, geography-based, environmental/sensor-based, and other metrics. Differential Evolution (DE) and Energy Transducers are proposed in [19, 20] as extensions to these models, with the goal of maximizing energy gains and hence improving energy efficiency and throughput in real-time networks. However, these models can only be used with a small number of inputs, limiting their capacity to be scaled. Multiband sensors based on triplexers and switching-based harvesting models are some of the methods studied in [21, 22, 23] for improving sensor efficiency for various kinds of sources. Nonlinear Energy Harvesting and high-efficiency RF models for low-complexity and high-speed harvesting processes are provided in [24, 25]. But these models require continuous reconfiguration of static rules, which limits their efficiency when applied to large-scale network scenarios. Moreover, most of these models also showcase higher complexity due to reconfiguration, which reduces their scalability performance. To overcome these limitations, next section proposes design of a novel Low-Complexity Energy Harvesting Model that uses Incremental Learning and Continuous Power Quality Optimization process. The model was evaluated on multiple scenarios, and compared with different state-of-the-art techniques which assists in its validation under different use cases.

3. Design of the proposed Low-Complexity Energy Harvesting Model via Incremental Learning and Continuous Power Quality Optimization process

Based on the brief review about energy harvesting models it was observed that existing models require continuous reconfiguration of static rules, which limits their efficiency when applied to large-scale network scenarios. Moreover, most of these models also showcase higher complexity due to reconfiguration, which reduces their scalability performance. To overcome these limitations, this section proposes design of a novel Low-Complexity Energy Harvesting Model that uses Incremental Learning and Continuous Power Quality Optimization process. Flow of the model is depicted in in figure 2, wherein it can be observed that the proposed model initially uses a Q-Learning based power evaluation method, that is capable of generating high-efficiency configurations of multisource harvesting devices. This is cascaded with design of a Particle Swarm Optimizer (PSO), that assists in performing continuous power quality optimizations.

The combined model is capable of selecting hybrid harvesting source configurations, and incrementally tune it for optimum harvesting performance. This is achieved via modelling a reward function that incorporates power gain along with low-complexity source selection process. The selection process is further enhanced via PSO based continuous learning for improving harvesting source configurations.

To perform these tasks, the model initially collects data from multiple devices that includes Harvesting Device Configurations, Performance Metrics from different Devices, and information about the harvesting sources. These information sets are processed via a Q-Learning based optimization model, which assists in identification of optimum device configurations under multisource scenarios.

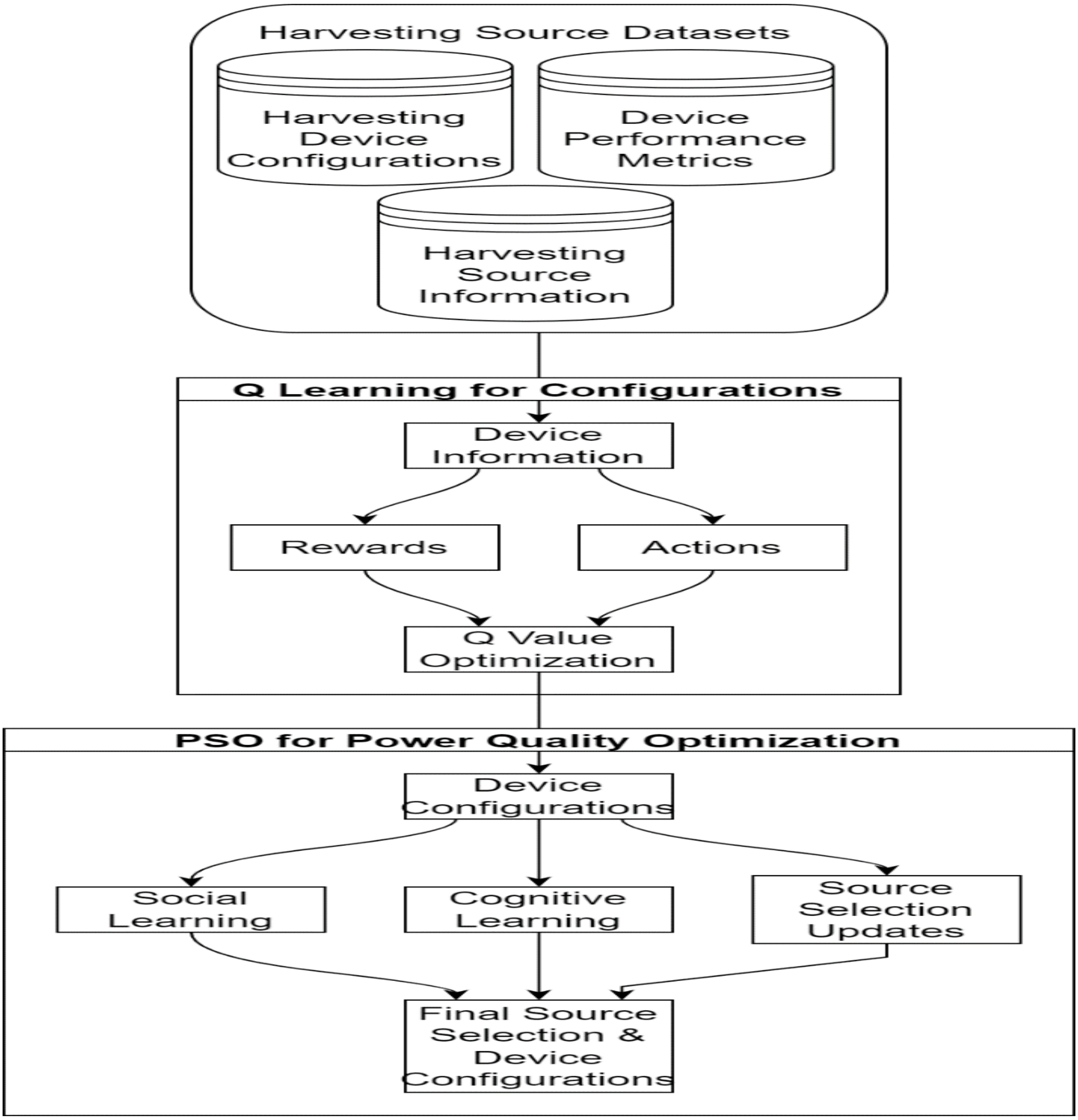

Figure 2. Design of the proposed model for continuous harvesting optimizations

The Q-Leaning model works via the following process,

- Initialize configurations for Maximum Power Point Tracking (MPPT) for different sources based on equation 1,

$$C(MPPT)_i = SP\left(Max\left(\bigcup P_{out}\right)\right)|_i \ldots (1)$$

Where, $C(MPPT)$ represents configuration of the MPPT devices, while SP represents corresponding sensor positions for i^{th} sensor, while P_{out} represents output power levels.

- Based on these configurations, estimate Q Values for each harvesting sensor via equation 2,

$$Q_i = \frac{P(C(MPPT)_i)}{Max(P_i)} \ldots (2)$$

Where, $P\big(C(MPPT)\big)$ represents power output due to current harvesting node's MPPT configuration, while $Max(P)$ represents maximum possible power levels.

- After each periodic interval, estimate New Q Value via equation 3,

$$Q(New) = Q + L_R * [R + D_R * Max(Q) - Q] \ldots (3)$$

Where, $Q(New)$ represents New Q Value, L_R represents learning rate, R represents reward, which is evaluated via equation 4, and D_R represents discount rate levels.

$$R = \frac{P(New)}{P(New) + P(Old)} \ldots (4)$$

Where, $P(New)$ represents output power due to new configuration of harvesting device, while $P(Old)$ represents corresponding output power due to old device configurations. The new configuration is obtained via modifying internal parameters of the harvesting device using a PSO based optimization process. This PSO Model works via the following process,

- Initialize the following parameters for PSO,
  - Total PSO Particles (N_p)
  - Total PSO Iterations (N_i)
  - Learning Rate for Cognitive process (L_c)
  - Learning Rate for Social Process (L_s)
- To start the optimization process, initially PSO generates a set of N_p particles, via the following process,
  - Generate stochastic configurations of each harvesting source via equation 5,

$$P(HS)_i = STOCH\left(Min\left(P_{HS_i}\right), Max\left(P_{HS_i}\right)\right) \ldots (5)$$

Where, $P(HS)$ represents parameter of the harvesting source, and its minimum & maximin value ranges, while $i \in (1, N_{ps})$, where, N_{ps} represents number of parameters for different harvesting sources.

  - Based on these configurations, identify particle position via equation 6,

$$P_i = \frac{\sum_{j=1}^{N_s} P_{out\,j}}{Max(P_{out})} \ldots (6)$$

Where, P_{out} & $Max(P_{out})$ represents power output & maximum power output levels for the i^{th} harvesting source respectively.

- Mark the current particle position as $PBest$, while mark maximum particle position as $GBest$, which will assist in social & cognitive learning processes.
- Iterate through N_i iterations, and generate new particle positions via equation 7,

$$P(New) = P(Old) * r + L_c * (P(Old) - PBest) + L_s(P(Old) - GBest) \ldots (7)$$

  Where, $P(New)$ is new particle position, while r is a stochastic number generated during optimization process.
- Update $PBest = PNew$, if $PBest > P(Old)$
- Based on this value of $PNew$, modify the harvesting source configurations, and update $GBest$

At the end of final iteration, identify particle with highest fitness levels, and use Its configuration for tuning performance of different harvesting sources. Based on this configuration, value of R is evaluated, and MPPT positions are changed to obtain better performance levels. This performance is evaluated in terms of response delay, harvested energy levels, throughput & packet delivery ratio, when applied to different energy harvesting wireless network scenarios. This performance can be observed from the next section of this text.

4. Results analysis & validation

The technique that has been proposed utilizes a combination of Q-Learning and a harvesting configuration aware PSO model. This combination helps to promote the ongoing growth of harvesting and communication performance levels. These levels are evaluated on a wireless network, where each node is connected to radio frequency (RF) harvesting sources, solar harvesting sources, and wind harvesting sources. These levels were established by applying a standard set of network characteristics to the network. The following is a report of these parameters, which may be found in table 1,

Harvesting Network Parameter	Value of Network Parameter
Uses harvesting sources	Solar, Wind, and RF
Model used for data propagation process	Two Ray Ground
Total nodes used for harvesting process	1000 to 2000
Network Size	3000m x 3000m
Power used for receiving packets	1 mW
Power used for transmitting packets	4 mW
Power used for sleep process	0.005 mW
Power used for transition process	0.1 mW
Delay for transition process	0.01 s
Initial level of energy for each of the harvesting nodes	3 W

Table 1. Network and node configurations

Based on these parameters, performance was evaluated in terms of harvesting delay (D), energy conserved during harvesting process (E), communication throughput due to harvesting (T), and Packet Delivery Ratio (P) due to harvesting process. These parameters were evaluated for different Number of Communications (NC), and were averaged across Solar, Wind & RF source types. These values were compared with [R1], [R2], and [R3], which assists in validating its performance under real-time scenarios. Based on this evaluation process, the harvesting delay can be observed from table 2 as follows,

EH NC	**Source D (ms) [R1]**	**Solar D (ms) [R2]**	**RF D (ms) [R3]**	**Wind D (ms) Proposed**
25	4.58	5.27	5.86	4.24
75	5.11	5.99	6.68	4.86
150	5.87	6.97	7.77	5.67
225	6.89	8.20	9.13	6.65
300	8.12	9.61	10.66	7.75
500	9.48	11.11	12.27	8.90
750	10.87	12.66	13.95	10.09
1000	12.28	14.30	15.72	11.30
1125	13.65	15.96	17.52	12.51
1250	14.92	17.56	19.27	13.67
1375	16.10	19.09	20.93	14.75
1500	17.14	20.44	22.39	15.72
1750	18.06	21.57	23.64	16.58
2000	19.08	22.79	24.97	17.52
2250	20.14	24.04	26.34	18.50
2500	21.27	25.36	27.79	19.54

Table 2. Average end-to-end delay for different communications (Solar, RF, & Wind based Harvesting Sources)

Based on this evaluation, it can be observed that the proposed model is 23.5% faster than [R1], 26.4% faster than [R2], and 28.5% faster than [R3] under Solar, RF & Wind based sources for power harvesting process. This performance optimization is possible due to use of low complexity PSO & Q-Learning models, which assist in improving harvesting performance under large-scale use cases. Based on similar strategy, energy harvesting performance can be observed from table 3 as follows,

EH NC	**Source E (mJ) [R1]**	**E (mJ) [R2]**	**E (mJ) [R3]**	**Solar E (mJ) Proposed**
25	11.23	16.76	14.77	21.90
75	11.83	17.60	15.50	22.78
150	12.39	18.44	16.25	23.86
225	12.98	19.34	17.04	25.04
300	13.62	20.29	17.87	26.24
500	14.28	21.26	18.67	27.34
750	14.96	22.06	19.18	27.92

1000	15.61	22.42	19.16	27.60
1125	16.20	22.40	18.71	26.62
1250	16.75	22.16	18.03	25.30
1375	17.30	21.89	17.41	24.14
1500	17.87	21.98	17.26	23.78
1750	18.47	22.55	17.66	24.32
2000	19.11	23.28	18.23	25.08
2250	19.74	24.11	18.89	25.98
2500	20.36	24.88	19.44	26.68

Table 3. Average energy consumption for different communications (Solar, RF, & Wind based Harvesting Sources)

Based on this evaluation, it can be observed that the proposed model has 16.5% higher energy harvesting efficiency than [R1], 8.5% higher energy harvesting efficiency than [R2], and 19.5% higher energy harvesting efficiency than [R3] under Solar, RF & Wind based sources for power harvesting process. This performance optimization is possible due to use of continuous power optimization based PSO & Q-Learning models, which assist in improving harvesting performance under large-scale use cases. Based on similar strategy, communication throughput can be observed from table 4 as follows,

EH	**Source**	**Solar**	**RF**	**Wind**
NC	**T (kbps) [R1]**	**T (kbps) [R2]**	**T (kbps) [R3]**	**T (kbps) Proposed**
25	1195	1247	1455	1600
75	1205	1258	1467	1614
150	1216	1268	1479	1627
225	1226	1279	1491	1641
300	1236	1289	1504	1654
500	1246	1300	1516	1668
750	1256	1310	1528	1681
1000	1266	1321	1540	1694
1125	1276	1331	1553	1708
1250	1286	1342	1565	1721
1375	1296	1352	1577	1735
1500	1306	1363	1589	1748
1750	1316	1373	1601	1761
2000	1327	1384	1614	1775
2250	1337	1394	1626	1788
2500	1347	1405	1638	1802

Table 4. Average throughput performance for different communications (Solar, RF, & Wind based Harvesting Sources)

Based on this evaluation, it can be observed that the proposed model showcases 23.5% higher throughput than [R1], 20.5% higher throughput than [R2], and 8.5% higher throughput than [R3] under Solar, RF & Wind based sources for power harvesting process. This performance optimization is possible due to use of continuous power optimization based PSO & Q-Learning models, which assist in improving harvesting performance under large-scale use cases. Based on similar strategy, Packet Delivery Ratio (PDR) can be observed from table 5 as follows,

EH	**Source**	**Solar**	**RF**	**Wind**
NC	**PDR (%) [R1]**	**PDR (%) [R2]**	**PDR (%) [R3]**	**PDR (%) Proposed**
25	74.20	73.86	74.70	87.84
75	74.82	74.48	75.32	88.58
150	75.45	75.10	75.96	89.32
225	76.09	75.73	76.59	90.06
300	76.72	76.36	77.22	90.80
500	77.35	76.98	77.85	91.54
750	77.98	77.61	78.48	92.28
1000	78.61	78.23	79.11	93.02
1125	79.24	78.85	79.74	93.76
1250	79.86	79.47	80.36	94.50
1375	80.49	80.09	80.99	95.24
1500	81.11	80.71	81.62	95.88
1750	81.73	81.33	82.24	96.43
2000	82.36	81.95	82.87	97.10
2250	82.99	82.58	83.50	97.76
2500	83.62	83.20	84.13	98.52

Table 5. Average packet delivery ratio performance for different communications (Solar, RF, & Wind based Harvesting Sources)

Based on this evaluation, it can be observed that the proposed model showcases 15.3% higher PDR than [R1], 15.5% higher PDR than [R2], and 14.5% higher PDR than [R3] under Solar, RF & Wind based sources for power harvesting process. This performance optimization is possible due to use of continuous power optimization based PSO & Q-Learning models, which assist in improving harvesting performance under large-scale use cases. Since of these improvements, the model may be utilized for large-scale harvesting network deployment scenarios because it shows higher harvesting performance under a variety of energy sources.

5. Conclusion and future work

The proposed model uses a combination of different energy sources, and performs source-dependent harvesting in order to optimize internal device configurations. These configurations are continuously evaluated, and checked in order to improve MPPT performance levels. This optimization is initiated by the Q-Learning model, and then continuously fine tuned by the PSO based optimization process. Due to which, the proposed model is able to achieve 23.5% faster harvesting performance than [R1], 26.4% faster harvesting performance than [R2], and 28.5% faster harvesting performance than [R3], it was also observed to achieve 16.5% higher energy harvesting efficiency than [R1], 8.5% higher energy harvesting efficiency than [R2], and 19.5% higher energy harvesting efficiency than [R3] under Solar, RF & Wind based sources for power harvesting process. In terms of communication performance, the model showcased 23.5% higher throughput than [R1], 20.5% higher throughput than [R2], and 8.5% higher throughput than [R3], it was also observed that the model was capable of achieving 15.3% higher PDR than [R1], 15.5% higher PDR than [R2], and 14.5% higher PDR than [R3] under Solar, RF & Wind based sources for power harvesting process. Because of these enhancements, the model is now suitable for usage in large-scale harvesting network deployment scenarios. This is possible due to the fact that it demonstrates improved harvesting performance when applied to a wide range of energy sources. In future, use of multiple bioinspired techniques along with deep learning models is recommended, which will assist in continuously optimizing model's performance under different energy sources. Moreover, the model must be validated on larger networks, and can be extended via use of incremental learning for real-time deployment scenarios.

References

1. H. Ko and S. Pack, "OB-DETA: Observation-based directional energy transmission algorithm in energy harvesting networks," in Journal of Communications and Networks, vol. 21, no. 2, pp. 168-176, April 2019, doi: 10.1109/JCN.2019.000015.
2. C. In, H. Kim and W. Choi, "Achievable Rate-Energy Region in Two-Way Decode-and-Forward Energy Harvesting Relay Systems," in IEEE Transactions on Communications, vol. 67, no. 6, pp. 3923-3935, June 2019, doi: 10.1109/TCOMM.2019.2901783.
3. H. Azarhava and J. Musevi Niya, "Energy Efficient Resource Allocation in Wireless Energy Harvesting Sensor Networks," in IEEE Wireless Communications Letters, vol. 9, no. 7, pp. 1000-1003, July 2020, doi: 10.1109/LWC.2020.2978049.
4. D. Altinel and G. Karabulut Kurt, "Modeling of Multiple Energy Sources for Hybrid Energy Harvesting IoT Systems," in IEEE Internet of Things Journal, vol. 6, no. 6, pp. 10846-10854, Dec. 2019, doi: 10.1109/JIOT.2019.2942071.
5. B. Zhao, J. Wang, W. -H. Liao and J. Liang, "A Bidirectional Energy Conversion Circuit Toward Multifunctional Piezoelectric Energy Harvesting and Vibration Excitation Purposes," in IEEE Transactions on Power Electronics, vol. 36, no. 11, pp. 12889-12897, Nov. 2021, doi: 10.1109/TPEL.2021.3083256.
6. S. Chamanian, S. Baghaee, H. Uluşan, Ö. Zorlu, E. Uysal-Biyikoglu and H. Külah, "Implementation of Energy-Neutral Operation on Vibration Energy Harvesting WSN," in IEEE Sensors Journal, vol. 19, no. 8, pp. 3092-3099, 15 April15, 2019, doi: 10.1109/JSEN.2019.2890902.
7. Y. Luo and L. Pu, "Practical Issues of RF Energy Harvest and Data Transmission in Renewable Radio Energy Powered IoT," in IEEE Transactions on Sustainable Computing, vol. 6, no. 4, pp. 667-678, 1 Oct.-Dec. 2021, doi: 10.1109/TSUSC.2020.3000085.
8. D. Altinel and G. K. Kurt, "Modeling of Hybrid Energy Harvesting Communication Systems," in IEEE Transactions on Green Communications and Networking, vol. 3, no. 2, pp. 523-534, June 2019, doi: 10.1109/TGCN.2019.2908086.

9. D. Newell and M. Duffy, "Review of Power Conversion and Energy Management for Low-Power, Low-Voltage Energy Harvesting Powered Wireless Sensors," in IEEE Transactions on Power Electronics, vol. 34, no. 10, pp. 9794-9805, Oct. 2019, doi: 10.1109/TPEL.2019.2894465.
10. Y. Wang, K. Yang, W. Wan, Y. Zhang and Q. Liu, "Energy-Efficient Data and Energy Integrated Management Strategy for IoT Devices Based on RF Energy Harvesting," in IEEE Internet of Things Journal, vol. 8, no. 17, pp. 13640-13651, 1 Sept.1, 2021, doi: 10.1109/JIOT.2021.3068040.
11. Q. Ren and G. Yao, "Enhancing Harvested Energy Utilization for Energy Harvesting Wireless Sensor Networks by an Improved Uneven Clustering Protocol," in IEEE Access, vol. 9, pp. 119279-119288, 2021, doi: 10.1109/ACCESS.2021.3108469.
12. Y. Yao, Z. Ni, W. Hu and M. Motani, "Optimizing Energy Harvesting Decode-and-Forward Relays With Decoding Energy Costs and Energy Storage," in IEEE Access, vol. 9, pp. 96613-96628, 2021, doi: 10.1109/ACCESS.2021.3092882.
13. H. Zhang, Y. -x. Guo, Z. Zhong and W. Wu, "Cooperative Integration of RF Energy Harvesting and Dedicated WPT for Wireless Sensor Networks," in IEEE Microwave and Wireless Components Letters, vol. 29, no. 4, pp. 291-293, April 2019, doi: 10.1109/LMWC.2019.2902047.
14. X. Wu, L. Tan and S. Tang, "Optimal Energy Supplementary and Data Transmission Schedule for Energy Harvesting Transmitter With Reliable Energy Backup," in IEEE Access, vol. 8, pp. 161838-161846, 2020, doi: 10.1109/ACCESS.2020.3021468.
15. Y. Sun, C. Song, S. Yu, Y. Liu, H. Pan and P. Zeng, "Energy-Efficient Task Offloading Based on Differential Evolution in Edge Computing System With Energy Harvesting," in IEEE Access, vol. 9, pp. 16383-16391, 2021, doi: 10.1109/ACCESS.2021.3052901.
16. M. Germer, U. Marschner and A. Richter, "Energy Harvesting for Tire Pressure Monitoring Systems From a Mechanical Energy Point of View," in IEEE Internet of Things Journal, vol. 9, no. 10, pp. 7700-7714, 15 May15, 2022, doi: 10.1109/JIOT.2022.3152547.
17. Khan et al., "EH-IRSP: Energy Harvesting Based Intelligent Relay Selection Protocol," in IEEE Access, vol. 9, pp. 64189-64199, 2021, doi: 10.1109/ACCESS.2020.3044700.
18. M. Q. Dinh and M. Thuy Le, "Triplexer-Based Multiband Rectenna for RF Energy Harvesting From 3G/4G and Wi-Fi," in IEEE Microwave and Wireless Components Letters, vol. 31, no. 9, pp. 1094-1097, Sept. 2021, doi: 10.1109/LMWC.2021.3095074.
19. M. Siddiqui, L. Musavian and S. Aïssa, "Time-Switching Energy Harvesting Communications: Harvesting Beneficialness and Performance Evaluation," in IEEE Transactions on Vehicular Technology, vol. 70, no. 10, pp. 11023-11027, Oct. 2021, doi: 10.1109/TVT.2021.3104744.
20. R. B. Roy et al., "A Comparative Performance Analysis of ANN Algorithms for MPPT Energy Harvesting in Solar PV System," in IEEE Access, vol. 9, pp. 102137-102152, 2021, doi: 10.1109/ACCESS.2021.3096864.
21. L. Pang et al., "Energy-Efficient Resource Optimization for Hybrid Energy Harvesting Massive MIMO Systems," in IEEE Systems Journal, vol. 16, no. 1, pp. 1616-1626, March 2022, doi: 10.1109/JSYST.2021.3074542.
22. P. Mayer, M. Magno and L. Benini, "Energy-Positive Activity Recognition - From Kinetic Energy Harvesting to Smart Self-Sustainable Wearable Devices," in IEEE Transactions on Biomedical Circuits and Systems, vol. 15, no. 5, pp. 926-937, Oct. 2021, doi: 10.1109/TBCAS.2021.3115178.

23. D. Ghosh, M. K. Hanawal and N. Zlatanov, "Learning to Optimize Energy Efficiency in Energy Harvesting Wireless Sensor Networks," in IEEE Wireless Communications Letters, vol. 10, no. 6, pp. 1153-1157, June 2021, doi: 10.1109/LWC.2021.3058170.
24. H. Saito, "Theoretical Analysis of Nonlinear Energy Harvesting From Wireless Mobile Nodes," in IEEE Wireless Communications Letters, vol. 10, no. 9, pp. 1914-1918, Sept. 2021, doi: 10.1109/LWC.2021.3086192.
25. D. Khan et al., "A High-Efficient Wireless Power Receiver for Hybrid Energy-Harvesting Sources," in IEEE Transactions on Power Electronics, vol. 36, no. 10, pp. 11148-11162, Oct. 2021, doi: 10.1109/TPEL.2021.3071374.