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ABLEH: Improving power efficiency via augmented bioinspired learning for energy harvesting in wireless networks

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ABSTRACT

Battery powered nodes in wireless networks (including internet of things (IoT)), require efficient harvesting models in order to improve their network lifetime. To perform this task, a wide variety of power sources including solar, wind, biomass, etc. are used along with node-to-node energy transfers. Most of these models utilize parametric selection for identification of the best node(s) for effective energy harvesting. These models utilize node location, energy levels, and other node-specific parameters to perform this task. But due to adhoc nature of nodes, the efficiency in estimation of these parameters is limited, thereby limiting the effectiveness of energy harvesting. Moreover, these models do not consider comprehensive parametric analysis, which limits their scalability, and performance for larger networks. In order to overcome these issues, this text proposes design of a novel augmented bioinspired learning for energy harvesting (ABLEH) in wireless networks. The proposed model utilizes a modified version of iterative Genetic Algorithm (MGA) for selection of the best energy harvesting nodes. The nodes are selected based on their temporal performance in terms of energy consumption, delay of energy transfer, link quality, and temporal harvesting efficiency. This selection is accompanied with augmented learning, wherein node-to-node distance decides whether MGA activation is needed or not, thereby assisting in further lifetime improvement. Due to exploration of these parameters, the proposed model is observed to showcase an energy efficiency of 8%, along with a delay reduction of 6%, and harvesting efficiency improvement of 9% when compared with various state-of-the-art methods. Moreover, the proposed model was tested under different network configurations, and showcases good performance, which is observed to be invariant of network size, network type, and node type. Furthermore, the proposed model is also observed to have better routing performance due to the effective node selection during harvesting process. This performance is also compared with various state-of-the-art harvesting techniques, and a 9% reduction in energy consumption, 5% improvement in throughput, and 8% improvement in network speed is observed. Based on these evaluations, it is observed that the proposed ABLEH Model is applicable for a wide variety of network configurations, which improves its deployment capabilities.

Keywords: Energy, harvesting, Genetic, Machine learning, Bioinspired

1. INTRODUCTION

Energy harvesting in wireless networks is a multidomain task which involves analysis of node parameters, analysis of network parameters, identification of most optimum harvesting sources, and their scheduling. These sources include alkaline batteries, super capacitors, photovoltaic sources, industrial solar solutions, thermoelectric components, vibration utilization via magnetic & piezoelectric sources. A typical energy harvesting model is depicted in figure 1, wherein different wireless nodes, along with their harvesting modes are visualized [1]. From this this model it can be observed that, Solar power is converted into electric form in order to charge node's battery. This power is then used for effectively shifting the node from sleep state to wake state, or to idle state depending upon network requirements.

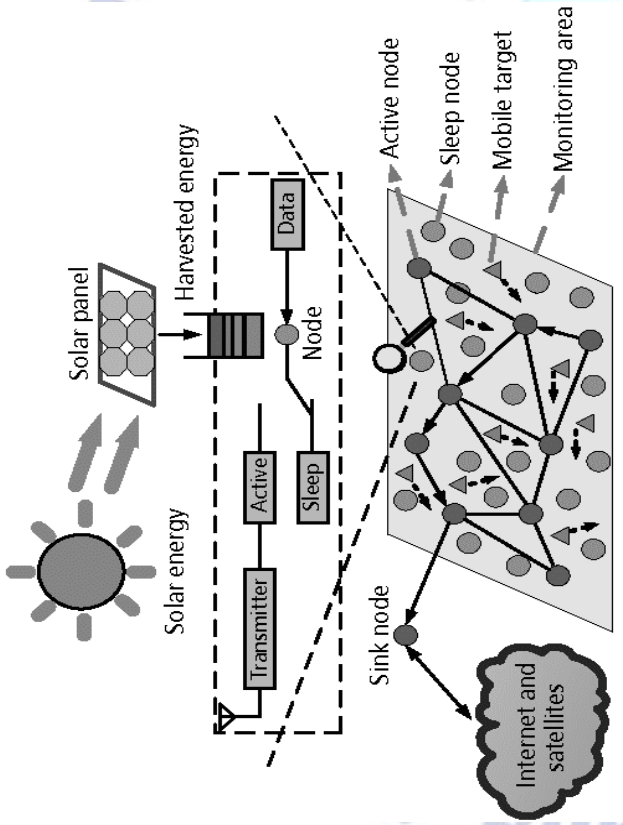

Figure 1. A typical energy harvesting model

The harvesting model is also capable of selecting Nodes that can transfer energy to other nodes for better communication efficiency. A wide variety of system models are proposed by researchers to perform this selection [2, 3, 4], and each of these models vary in terms of energy efficiency, harvesting delay, application of harvesting, etc. A brief survey of these models is discussed in the next section, which describes some of the recently proposed energy harvesting techniques, along with their nuances, advantages, characteristics, and future research scopes. From this review, it is observed that recently proposed models are highly application specific, and have limited scalability capabilities. In order to improve these capabilities, a novel augmented bioinspired learning for energy harvesting (ABLEH) model is proposed in section 3 of this text. The proposed model is capable of improving network lifetime, via increasing harvesting capabilities of high-capacity nodes. The Multiple objective GA Model is also capable of selecting an optimum route for communication, which assists in reducing delay needed for data routing. In order to validate this performance, section 4 evaluates energy consumption, harvesting efficiency, & end-to-end delay parameters, and compares them with various state-of-the-art harvesting models. Finally, this text concludes with some interesting observations about the proposed model, and recommends methods to further improve its performance.

2. LITERATURE REVIEW

A wide variety of models are proposed for energy harvesting in wireless networks, and each of them vary in terms of efficiency of harvesting, network quality of service (QoS), and application of deployment. For instance, the work in [5,6] proposes models for two-way decode-and-forward energy harvesting & hybrid harvesting schemes for improving accuracy of harvesting. These schemes identify best models suited for any given environment in order to map harvesting nodes with sources. These models have low QoS due to congestion & collision issues. The QoS can be improved via energy-saving link scheduling (ESLS) as discussed in [7], wherein researchers have showcased use of link quality for improving transfer of energy between different harvesting nodes. Similar models are proposed in [8, 9, 10], wherein device-selective energy request (DSER), data & energy integrated network model (DEINM), and combination of Dinkelbach method with conditions of Karush-Kuhn-Tucker (KKT) is evaluated. These models aim at reducing redundancy during transfer of energy, which assists in maximum power utilization. Performance of these models is further

extended in [11, 12, 13], wherein combination of RF energy with wireless power transfer, Nonlinear energy harvesting, and low-power energy transfer models are discussed. These models assist in selecting most probable communication nodes, which can be used for high-performance energy transfer with minimum delay. Due to which efficiency of harvesting, and network QoS is incrementally improved. A novel Uneven Clustering Protocol (UCP) is proposed in [14], which assists in enhancing utilization of harvested energy via grouping nodes with similar energy signatures. These protocols allow for better energy efficiency when compared with non-cluster-based models, and thus can be used for large-scale network deployments.

Models that provide fine grained improvement in performance of energy harvesting are discussed in [15, 16, 17, 18], wherein throughput enhancement, directional energy transmission algorithm (DETA), Upper Confidence Bound (UCB) model, and time-synchronized channel hopping (TSCH) based Network joining models are defined. These models assist in improving end-to-end charging and discharging capabilities via deciding charging & discharging rates for a wide variety of network applications. Similarly, switched supercapacitor circuits [19], Neutral vibration energy harvesting [20], suboptimal harvested power control using Q-learning & machine learning augmentations [21], design of super-capacitor with RF transceiver module [22], and Multiband Ambient RF energy harvesting [23] are defined by researchers. These models assist in reducing energy leakage via use of multiple energy conservation sources, which assists in enhancing network's harvesting capacity. Thus, based on this discussion it can be observed that reviewed models are highly source & context-dependent, which limits their scalability to small & medium scale networks. In order to improve this efficiency, a novel augmented bioinspired learning model for energy harvesting in wireless networks is discussed in the next section of this text. Performance of this model is estimated on different simulation scenarios, which assist in identification of best harvesting and routing practices for wireless networks.

3. DESIGN OF THE PROPOSED AUGMENTED BIOINSPIRED LEARNING MODEL FOR ENERGY HARVESTING IN WIRELESS NETWORKS

Based on the literature review, it can be observed that recently proposed models for energy harvesting are largely network specific & can be used with specific harvesting sources. Due to which their scalability is limited, which further limits their real-time network performance. In order to improve network scalability, this section proposes design of an augmented bioinspired learning model for energy harvesting in wireless networks. The model design can be observed from figure 2, wherein its internal data flow is visualized. The proposed model aggregates data from various sources which includes information about network parameters, energy harvesting sources, and node parameters. This information is fed into a multiple objective GA model, which results into 2 solutions, one is targeted towards selection of best harvesting strategy & the other is targeted towards route selection. Results from both solutions are used for network deployment, which assists in design of a highly energy efficient, low power and low delay energy harvesting wireless network. Performance of this network is continuously evaluated in terms of quality of service (QoS) parameters like end-to-end delay, throughput, energy consumption, and packet delivery ratio (PDR). A temporal analysis method is applied to these parameters, which assists in incrementally tuning underlying GA performance.

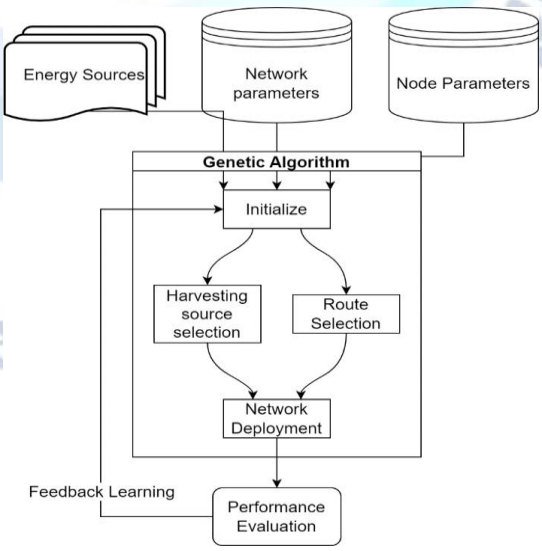

Figure 2. Design of the proposed bioinspired model for efficient energy harvesting in wireless networks

Design of this performance evaluation layer is of primary importance, because real-time network deployments are high adhoc in nature. Due to this adhoc nature, multiple run-time changes are observed in wireless network, which are mitigated via continuous tuning of the underlying GA model. Design of these internal components is described in different sub-sections of this text, which will assist readers to implement these models in parts or as a whole for their network deployments.

3.1. Design of proposed augmented bioinspired learning for energy harvesting via multiple objective GA

Node parameters including node locations, energy levels, per unit charging delay, per unit discharging delay, and temporal packet delivery performance, are combined with network-level parameters. These include, network size, maximum hops supported by the network, & node-to-node link quality, which are evaluated continuously at run-time during every network communication. The GA model uses these parameters, and combines them with harvester information including number of energy sources, capacity of each source, source charging time, and source discharging efficiency. These parameters are used by the multiple objective GA model in order to identify best nodes for routing, and most optimum node-to-harvesting source mapping for improving network energy efficiency. Design of the proposed multiple objective GA model is depicted in figure 3, wherein their internal working details can be observed.

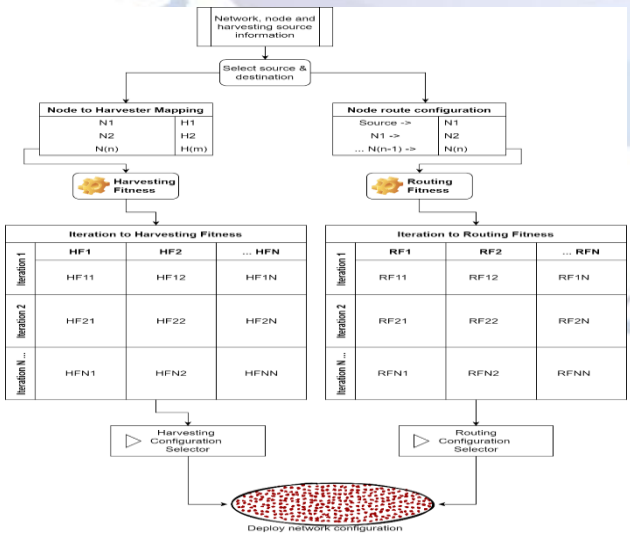

Figure 3. Design of the multiple objective GA model for selection of harvesting & routing configuration

The multiple objective GA model works via the following process,

- Select a source & destination node to perform routing & harvesting operations
- Initialize GA parameters, which include,
  - Number of iterations (N_i)
  - Number of solutions (N_s)
  - Learning rate for routing ($L_{r_{route}}$)
  - Learning rate for harvesting ($L_{r_{harvest}}$)
  - Maximum hops allowed for routing (Max_{hops})
  - Number of harvesting sources available ($N_{harvest}$)
- Mark all the solutions as 'to be modified'
- For each iteration in 1 to N_i
  - For each solution in 1 to N_s
    - If the solution is marked as 'not to be modified', then skip it, and go to next solution.
    - Else, generate a new solution using the following steps,
      - Select a random harvesting source via equation 1,

$$H_{source} = RAND(1, N_{harvest}) \dots (1)$$

      - Select a stochastic routing configuration via equation 2,

$$Route = \bigcup_{i=1}^{Max_{hops}} Unique\big(RANDOM(1, NN)\big) \dots (2)$$

Where, NN represents number of nodes in the network. A node is selected on the routing path, if it satisfies the following condition,

$$D(N_s) < D(s_d) \; and \; D(N_d) < D(s_d) \dots (3)$$

Where, $D(N_s)$ represents distance between selected node, and the source, while d represents destination node. This condition validates that the currently selected node is in the routing path between source & destination nodes.

      - Using this selection, evaluate harvesting solution fitness via equation 4 as follows,

$$f_{h_i} = \frac{D_{H_{source}}}{Max_D} + \frac{Max_{H_{cap}}}{Cap_{H_{source}}} + \frac{Max_{DE}}{DE_{H_{source}}} \dots (4)$$

Where, f_{h_i} represents harvesting fitness, $D_{H_{source}}$ represents delay needed for charging the source,

$Cap_{H_{source}}$ represents capacity of the selected source, and $DE_{H_{source}}$ represents discharging efficiency of the selected source.

- Similarly, evaluate routing solution fitness via equation 5 as follows,

$$f_{routin\ g_i} = \sum_{i=1}^{Route} \frac{Dist_{i,i+1}}{Max_{Dist}} + \frac{Max_e}{E_i} + \frac{100}{PDR_i} + \frac{R_{dis\ i}}{Max_{R_{dis}}} + \frac{Max_{LQ}}{LQ_{i,i+1}} \ldots (5)$$

Where, $Dist, E, PDR, R_{dis}, and\ LQ$ represents distance between nodes, residual node energy, packet delivery ratio of node, discharging rate of selected node, and link quality between nodes.

- These fitness values are evaluated for each solution, and fitness threshold for harvesting is evaluated via equation 6,

$$f_{th_{harvest}} = \sum_{i=1}^{N_s} f_{h_i} * \frac{L_{r_{harvest}}}{N_s} \ldots (6)$$

- Fitness threshold for routing is evaluated via equation 7 as follows,

$$f_{th_{route}} = \sum_{i=1}^{N_s} f_{rout\ e_i} * \frac{L_{r_{route}}}{N_s} \ldots (7)$$

- Based on this threshold, solutions are marked as 'to be modified', and 'not to be modified', via the following conditions,
  - If fitness of a solution is less than both $f_{th_{harvest}}$ & $f_{th_{route}}$ then mark the solution as 'not to be changed'
  - If fitness of a solution is less than $f_{th_{harvest}}$ but more than $f_{th_{route}}$ then mark the solution as 'to be changed'
  - If fitness of a solution is more than $f_{th_{harvest}}$ but less than $f_{th_{route}}$ then select a new source, and re-check value of fitness w.r.t. $f_{th_{harvest}}$, it is lower, then mark this solution as 'not to be changed', else mark this solution as 'to be changed'
  - If fitness of a solution is more than both $f_{th_{harvest}}$ & $f_{th_{route}}$ then mark the solution as 'to be changed'
  - Repeat this process for all iterations, and select the solution where minimum value of fitness for both routing and harvesting are obtained

Via this process, solutions with optimum harvesting source for a given node, and optimum route are selected. This process is repeated for every network communication in order to formulate routing & harvesting rules in the network. These rules are updated using a continuous evaluation layer, which assists in improving network performance. Design of continuous evaluation layer is discussed in the next section of this text.

3.2. Design of continuous evaluation layer for performance improvement

Once the network is deployed, and has been evaluated for multiple iterations, then its performance measures are estimated. These measures include, end-to-end delay, communication throughput, energy requirement, packet delivery ratio, and average node-level energy discharge delay. Based on these values, an incremental factor for each entity is evaluated via 8, 9, 10, 11, and 12 as follows,

$$\partial_{delay} = \frac{\sum_{i=1}^{N_c} D_i}{\sum_{j=1}^{N_{c_{prev}}} D_{j_{prev}}} \ldots (8)$$

$$\partial_{TH} = \frac{\sum_{i=1}^{N_{c_{prev}}} TH_{i_{prev}}}{\sum_{j=1}^{N_c} TH_j} \ldots (9)$$

$$\partial_{PDR} = \frac{\sum_{i=1}^{N_{c_{prev}}} PDR_{i_{prev}}}{\sum_{j=1}^{N_c} PDR_j} \ldots (10)$$

$$\partial_e = \frac{\sum_{i=1}^{N_{c_{prev}}} E_{i_{prev}}}{\sum_{j=1}^{N_c} E_j} \ldots (11)$$

$$\partial_{dela\ y_{dis}} = \frac{\sum_{i=1}^{N_c} D_{dis\ i}}{\sum_{j=1}^{N_{c_{prev}}} D_{dis\ j_{prev}}} \ldots (12)$$

Where, $N_c, \& N_{c_{prev}}$ represents current number of communications, and previous number of communications, while, $D, TH, PDR, E, and\ D_{dis}$

represents average end-to-end delay, throughput, packet delivery ratio, energy consumption, and node-level energy discharge delay during these communications. Based on these incremental values, learning rates for routing & harvesting are modified. This modification assists in continuous learning, which results in better QoS & harvesting performance in the network. The new value of learning rate for harvesting is estimated via equation 13 as follows,

$$L_{r_{harvest\ new}} = L_{r_{harvest}} * \frac{[\partial_e + \partial_{delay_{dis}}]}{2} \ldots (13)$$

Similarly, the value of learning rate for routing is estimated via equation 14 as follows,

$$L_{r_{route_{new}}} = L_{r_{route}} * \frac{[\partial_{TH} + \partial_{PDR} + \partial_e]}{\partial_{delay} + 2} \ldots (14)$$

Based on these new values, the multiple objective GA model is tuned, and network efficiency is continuously improved. This efficiency is estimated using standard routing configurations, and compared with various state-of-the-art methods, as discussed in the next section of this text.

4. RESULTS ANALYSIS & VALIDATION

The proposed energy harvesting & route optimisation protocol uses augmentation of multiple objective GA with incremental learning. Due to which, its routing & energy harvesting performance is improved. In order to evaluate this performance, a standard network configuration is used. This configuration

Channel Type: Wireless Multi-Channel

Propagation Model: Two Ray Ground

Network interface: Wireless Physical

MAC Protocol: Mac/802.16

Number of nodes:125 to 500

Routing protocol: AOMDV

Network X Size: 500

Network Y Size: 500

Number of energy sources 3

Type of sources Solar, Wind, Vibration

Packet Size: 1000 bytes per packet

Packet Interval: 0.01 seconds per packet

Using these standard wireless network parameters, analysis of end-to-end communication delay, energy requirement during communication, and efficiency of harvesting were estimated. The efficiency of harvesting was calculated via equation 15 as follows,

$$E_{harvest} = \sum_{i=1}^{N_s} \frac{1 - P_{s_i}}{P_{t_i}} \ldots (15)$$

Where, $N_s, P_s, and\ P_t$ represents number of harvesting sources, power stored on the source, and total power capacity of the source. These parameters were compared with DSER [8], UCP [14], and DETA [16] in order to validate performance of the current implementation. Using the current configuration, end-to-end delay is tabulated in table 1 as follows,

Num. Nodes	Delay (ms) DSER [8]	Delay (ms) UCP [14]	Delay (ms) DETA [16]	Delay (ms) ABLEH
125	0.43	0.45	0.36	0.31
150	0.53	0.48	0.42	0.36
175	0.64	0.63	0.53	0.45
200	0.74	0.73	0.62	0.52
225	0.85	0.81	0.69	0.59
250	0.96	0.94	0.78	0.67
275	1.06	1.03	0.87	0.74
300	1.60	1.55	1.31	1.11
375	2.12	2.07	1.75	1.49
400	1.91	1.86	1.57	1.33

438	2.09	2.03	1.72	1.46
475	2.28	2.21	1.87	1.59
500	2.46	2.39	2.02	1.72

Table 1. End-to-end communication delay in the network

From the evaluations done in table 1, it can be observed that end-to-end delay has been reduced by 26% when compared with DSER [8], 24% when compared with UCP [14], and 15% when compared with DETA [16] system implementations. Due to this improvement, the system is useful for a wide variety of high-speed network applications. Similar performance evaluation is done for energy consumption in the network, and can be observed from table 2 as follows,

Num. Nodes	E (mJ) DSER [8]	E (mJ) UCP [14]	E (mJ) DETA [16]	E (mJ) ABLEH
125	5.83	6.71	5.02	4.39
150	6.49	7.47	5.59	4.89
175	6.82	7.84	5.86	5.13
200	8.47	10.27	7.50	6.56
225	9.41	11.37	8.32	7.27
250	10.73	12.64	9.35	8.18
275	11.85	14.29	10.45	9.15
300	17.82	21.27	15.64	13.68
375	23.74	28.36	20.83	18.23
400	21.07	25.30	18.54	16.23
438	23.03	27.69	20.29	17.75
475	25.00	30.07	22.03	19.27
500	26.96	32.46	23.77	20.80

Table 2. Energy consumption during routing process

Via this evaluation it is observed that overall network lifetime is improved by almost 30% when compared with DSER [8], 39% when compared with UCP [14], and 14.2% when compared with DETA [16] which makes the model highly applicable for a wide variety of low-power applications. Similar performance evaluation is done for communication throughput in the network, and can be observed from table 3 as follows,

Num. Nodes	Thr. (kbps) DSER [8]	Thr. (kbps) UCP [14]	Thr. (kbps) DETA [16]	Thr. (kbps) ABLEH
125	353.1	307.0	440.1	423.2
150	368.5	320.4	459.3	441.6
175	370.7	322.3	462.0	444.3
200	470.4	443.2	609.1	585.7
225	517.6	482.7	666.9	641.2
250	592.8	535.0	751.9	722.9
275	653.2	608.7	841.3	808.9
300	983.7	903.5	1258.1	1209.7
375	1309.5	1204.2	1675.8	1611.4
400	1154.2	1069.9	1482.8	1425.7
438	1260.2	1169.9	1620.1	1557.8
475	1366.2	1270.0	1757.4	1689.9
500	1472.2	1370.0	1894.8	1821.9

Table 3. Throughput performance during routing process

Via this evaluation it is observed that overall network throughput is improved by almost 15% when compared

with DSER [8], 19% when compared with UCP [14], and 8% when compared with DETA [16] which makes the model highly applicable for a wide variety of high-throughput applications. Similar performance evaluation is done for packet delivery ratio (PDR) in the network, and can be observed from table 4 as follows,

Num. Nodes	PDR (%) DSER [8]	PDR (%) UCP [14]	PDR (%) DETA [16]	PDR (%) ABLEH
125	83.73	83.81	83.77	96.65
150	83.90	83.98	83.94	96.85
175	84.07	84.15	84.11	97.05
200	84.11	84.32	83.81	97.01
225	84.24	84.41	84.07	97.19
250	84.28	84.58	84.24	97.34
275	84.29	84.75	84.41	97.48
300	84.33	84.79	84.58	97.57
375	84.41	84.83	84.66	97.65
400	84.54	85.06	84.72	97.81
438	84.61	85.20	84.82	97.94
475	84.69	85.33	84.93	98.06
500	84.77	85.46	85.04	98.18

Table 4. PDR performance during routing process

Via this evaluation it is observed that overall network PDR is improved by almost 14% when compared with DSER [8], 12.5% when compared with UCP [14], and 12.7% when compared with DETA [16] which makes the model highly applicable for a wide variety of high-efficiency applications. Similar performance evaluation is done for efficiency of harvesting (EH) in the network, and can be observed from table 5 as follows,

Num. Nodes	EH (%) DSER [8]	EH (%) UCP [14]	EH (%) DETA [16]	EH (%) ABLEH
125	86.10	88.49	89.50	98.12
150	86.23	88.65	89.58	98.25
175	86.33	88.80	89.66	98.38
200	86.39	88.96	89.74	98.49
225	86.45	89.08	89.94	98.63
250	86.49	89.19	90.10	98.75
275	86.55	89.32	90.23	98.87
300	86.64	89.44	90.34	98.98
375	86.73	89.58	90.44	99.10
400	86.82	89.75	90.54	99.24
438	86.90	89.89	90.65	99.36
475	86.98	90.03	90.77	99.49
500	87.06	90.17	90.88	99.61

Table 5. Efficiency during harvesting process

Via this evaluation it is observed that overall network harvesting efficiency is improved by almost 12.5% when compared with DSER [8], 8.6% when compared with UCP [14], and 8.3% when compared with DETA [16] which makes the model highly applicable for a wide variety of high-efficiency applications. Due to these improvements, the model is highly useful for energy harvesting, and improving routing efficiency for multiple scale application scenarios.

5. CONCLUSION AND FUTURE WORK

The proposed ABLEH model combines design of multiple objective GA with continuous learning & feedback mechanism for performance tuning. Due to

which, the proposed model is capable of responding to real-time network changes, which assists in improving its node-level scalability, and large-scale deployment capabilities. Due to the use of an automatically tuned GA model, the proposed ABLEH method's end-to-end delay has been reduced by 26% when compared with DSER [8], 24% when compared with UCP [14], and 15% when compared with DETA [16], due to which, overall network throughput is improved by almost 15% when compared with DSER [8], 19% when compared with UCP [14], and 8% when compared with DETA [16] which makes the model highly applicable for a wide variety of high-throughput & low delay applications. Furthermore, it is observed that overall network lifetime is improved by almost 30% when compared with DSER [8], 39% when compared with UCP [14], and 14.2% when compared with DETA [16] which makes the model highly applicable for a wide variety of low-power applications. In terms of energy harvesting, it is observed that overall network harvesting efficiency is improved by almost 12.5% when compared with DSER [8], 8.6% when compared with UCP [14], and 8.3% when compared with DETA [16] which makes the model highly applicable for a wide variety of high-efficiency applications. In future, researchers can extend this model via use of deep learning & Q-learning based methods, which will assist in further reducing network-level redundancies, and improving harvesting efficiency, and QoS performance for multiple network scenarios.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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