Performance Analysis Of Random Forest With Particle Swarm Optimization Model Employed In Lora Sensor Energy Consumption Optimization

Silas Abraham Friday[1]

Department of Electrical/ Electronic Engineering
Adekeke University, Ede Osun State, Nigeria
silas.abraham@adelekeuniversity.edu.ng

Emmanuel Ubom[2]
Department of Electrical and Electronic Engineering,
Akwa Ibom State University, Ikot Akpaden,
Mkpat Enin, Akwa Ibom State.
[1]emmanuelubom@aksu.edu.ng, [2]ubongukommi@aksu.edu.ng

Agbaji Adai Samuel [3]

Department of Computer Engineering
University of Uyo,
Uyo,Akwa Ibom State, Ngeria
agajisam@yahoo.com

***Abstract*— In this work, performance analysis of Random Forest (RF) with Particle Swarm Optimization (PSO) model employed in LoRa sensor energy consumption optimization is presented. The transmission distance is selected first and then, the RF model is trained to select the set of LoRa transceiver parameters values that can be used to transmit the data packet over that selected distance with minimal energy. The output from the RF model is the baseline solution. The search result from the RF model is further fine-tuned by applying PSO algorithm which is termed RF+PSO model. The results showed that the baseline RF solution requires more energy to transmit over a given TD than the RF+PSO based option. At TD of 886.98 m, the RF baseline solution has energy consumption of 3.4736 mJ while the RF+PSO has energy consumption of 3.11 mJ which is 10.47% reduction in energy consumption. Also, the RF + PSO model maintained higher packet deliver ratio (PDR) value from 96 % at TD of 10.85 m to 56 % at TD value of 886.98 m. In the same TD range, the baseline RF model has PDR value from 95 % at TD of 10.85 m to 7 % at TD value of 886.98 m. The results showed that the enhance RF+PSO model maintained overall better performance than the baseline RF model. As such, the enhance RF+PSO model is recommended for LoRa sensor energy consumption optimization for all the TD values.**

Keywords—LoRa Sensor, Random Forest, Particle Swarm Optimization Model, Energy Consumption Optimization, Packet Delivery Ratio

1. Introduction

In wireless sensor networks, energy consumption of the sensor nodes is one of the critical factors that are considered during the network design [1,2,3]. This is due to the resource constrained nature of the sensor nodes [4,5]. In most cases, the sensors are powered using battery with finite capacity which means that as the sensors operate and deplete the energy stored in the battery, there comes a time when the stored energy is exhausted and the node dies or goes out of operation [6,7,8]. In view of this, wireless sensor network designers seek to extend the battery lifespan by adopting energy efficient techniques [9,10,11]. One of such approaches is to control the sensor energy consumption [12].

Accordingly, this work presents an optimal energy consumption model for the sensor node. The solution presented in this work is combination of Random Forest (RF) and Particle Swarm Optimization (PSO) model. The RF provides the baseline solution that selects the sensor node parameters that will give the lowest energy consumption based on the available dataset used in the model training [13,14]. The PSO algorithm is then used to fine tune the solution provided by the RF model. In this way a more accurate optimal solution is realized. The solution presented in this work is essential since in practice the sensor may be deployed in remote locations that are very difficult to access. Hence, extending the battery lifetime through efficient energy consumption model can reduce the cost of replacing the sensor battery.

2. Methodology

In the present study, Random Forest (RF) model is used in optimizing the energy that can be used by the LoRa sensor to transmit data packets over a given transmission distance. The transmission distance is selected first and then, the RF model is trained to select the set of LoRa transceiver parameters values that can be used to transmit the data packet over that selected distance with minimal energy. The output from the RF model is the baseline solution. The search result from the RF model is further fine-tuned by applying particle swarm optimization (PSO) algorithm, as shown in Figure 1. T

In this research work, the PSO is identified as a multi-agent search scheme which carries along swarm of particles where each particle represents a potential solution which denotes the combination of parameters such as spreading factor, coding rate, bandwidth, and duty cycle. Each of the particles is allowed to traverse through a manifold search space while they updates their position based on previous experience. Each particle is initialized with value obtained from the RF model; these values are further evaluated to obtain the fitness of the function, the local optimal of each particle, and the global optimal of each particle. Once the optimal solution is obtained, the algorithm computes the optimal solution by modifying the velocity of the leading particle based on its local optimal and global optimal, then updating the trailing particles based on the active velocity. The position of the particles are denoted by the current values of the parameters (spreading factor denoted as SF, coding rate denoted as CR, bandwidth denoted as BW, and duty cycle denoted as DC), while the velocity is represented by the rate of change of these values; in other words, the rate at which these values are modified by the algorithm.

Notably two major considerations are given while using the PSO algorithm to select the optimal parameter configuration for optimal energy consumption in the LoRa network. These are: constraint handling and convergence check. For constraints handling, care is taken to ensure that the parameter values remain within their valid ranges by applying suitable boundary conditions. The iteration count is selected such that the iteration converges to a solution. The number of iteration can be dynamically adjusted to suit this. Two criteria which are used to check for optimal parameter configuration when using the PSO algorithm are: minimal changes in global best position, and reaching the maximum number of iterations.

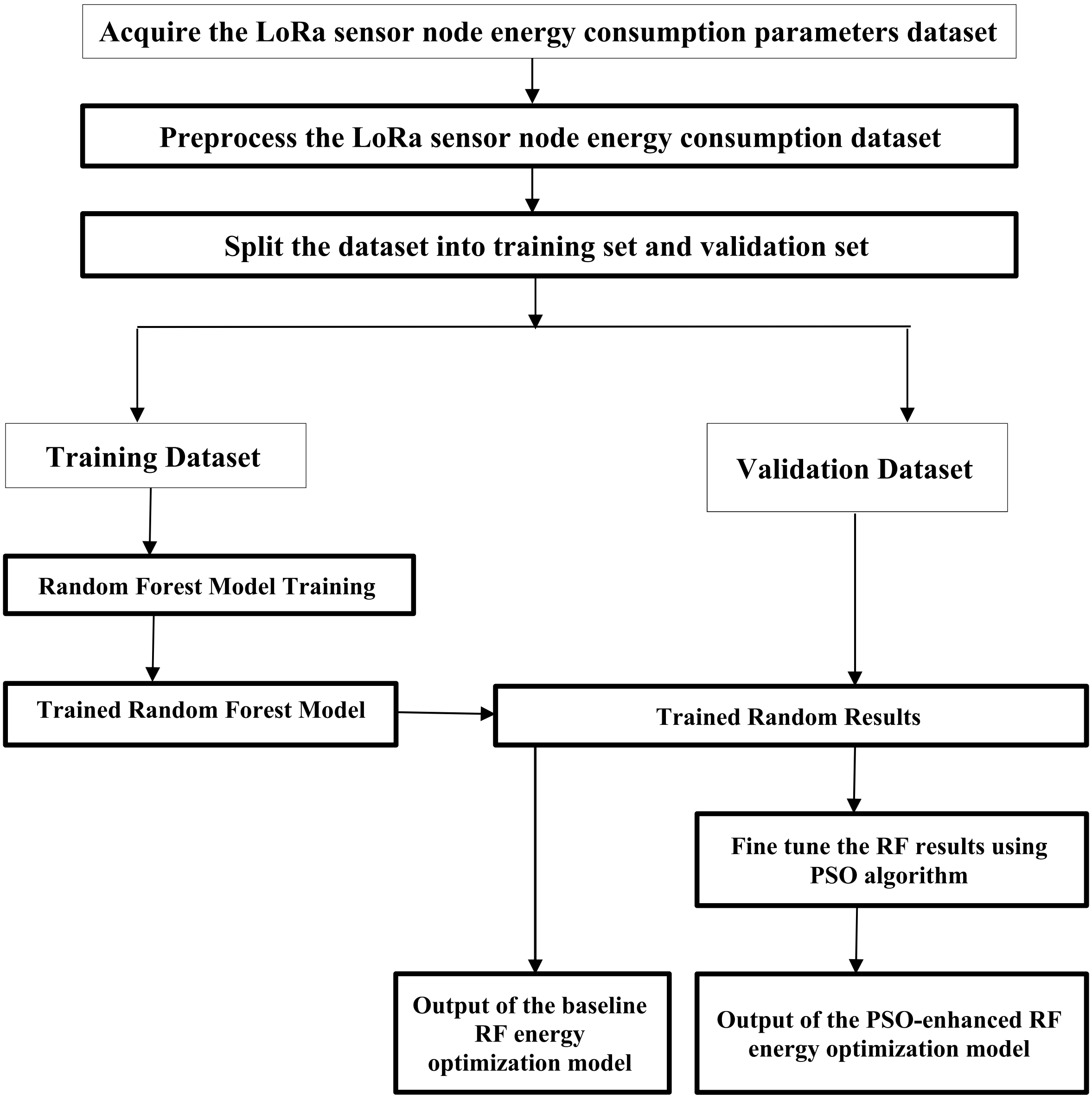
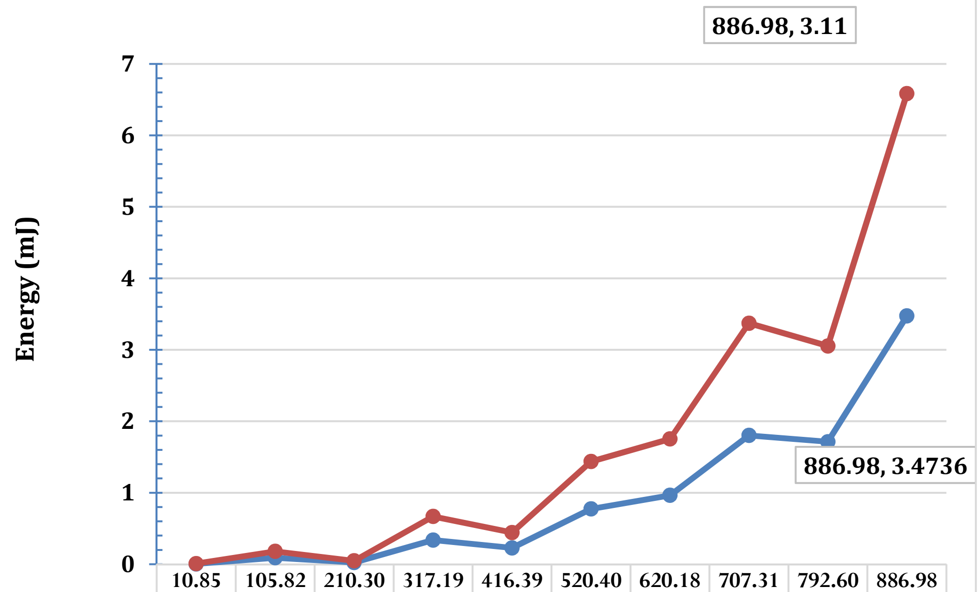


Figure 1 The flow diagram of the research procedure

3. Results and discussion

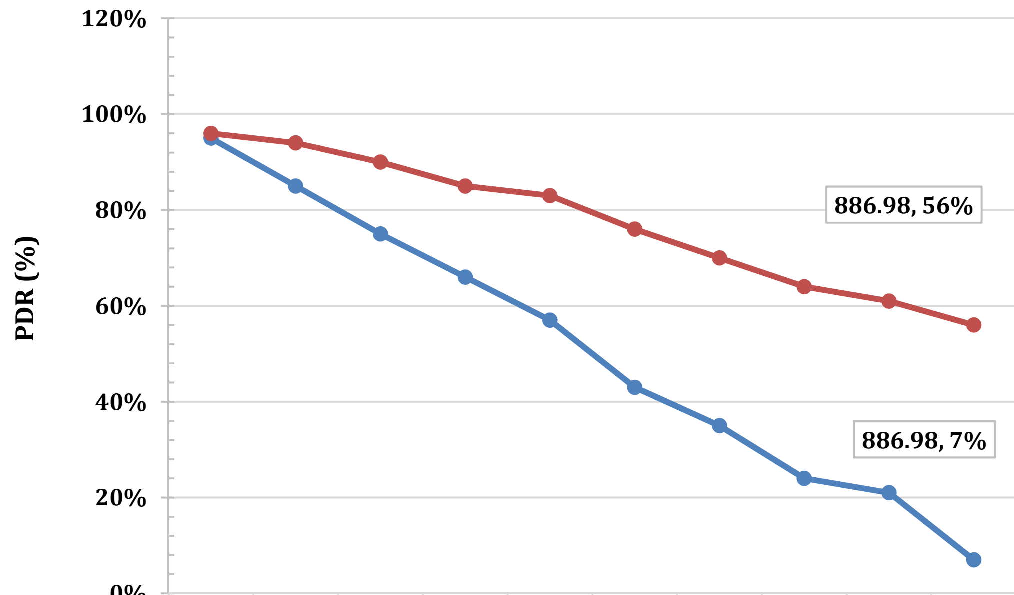
The results obtained using only the RF model is the baseline result which is compared with the results obtained after the application of the PSO algorithm. The graph of the energy that is used by the LoRa sensor to transmit data packets over the given transmission distance (TD) is presented in Figure 2 for both the RF baseline solution and the RF+PSO based option. The results showed that the baseline RF solution requires more energy to transmit over a given TD than the RF+PSO based option. At TD of 886.98 m, the RF baseline solution has energy consumption of 3.4736 mJ while the RF+PSO has energy consumption of 3.11 mJ which is 10.47% reduction in energy consumption.



	10.85	105.82	210.30	317.19	416.39	520.40	620.18	707.31	792.60	886.98
Energy (mJ) for RF + PSO	0.005	0.0893	0.0235	0.33	0.215	0.663	0.788	1.57	1.34	3.11
Energy (mJ) for RF	0.0037	0.0902	0.0242	0.3381	0.2274	0.7732	0.9644	1.8016	1.7139	3.4736

Figure 2 The graph of the energy that is used by the LoRa sensor to transmit data packets over the given transmission distance (TD)

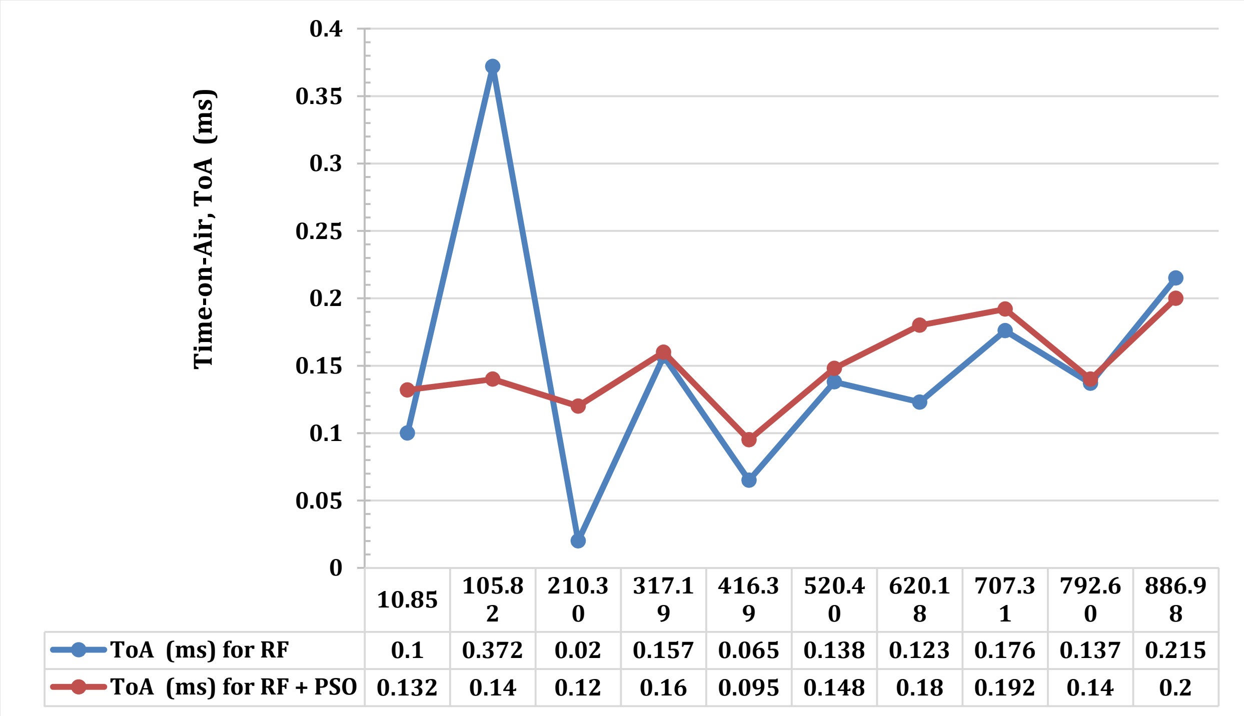
The line graph of the packet deliver ratio (PDR) achieved by the LoRa sensor when it transmits data packets over the given transmission distance (TD) is presented in Figure 3. It shows that the PDR is highest at low transmission distance but the PDR drops as the distance increases. In any case, the RF + PSO model maintained higher PDR value from 96 % at TD of 10.85 m to 56 % at TD value of 886.98 m. In the same TD range, the baseline RF model has PDR value from 95 % at TD of 10.85 m to 7 % at TD value of 886.98 m. There is therefore, over 49 % improvement in the PDR at the higher TD when the RF + PSO model is applied.



	10.85	105.82	210.30	317.19	416.39	520.40	620.18	707.31	792.60	886.98
PDR (%) for RF	95%	85%	75%	66%	57%	43%	35%	24%	21%	7%
PDR (%) for RF + PSO	96%	94%	90%	85%	83%	76%	70%	64%	61%	56%

Figure 3 The packet deliver ratio (PDR) achieved by the LoRa sensor when it transmits data packets over the given transmission distance (TD)

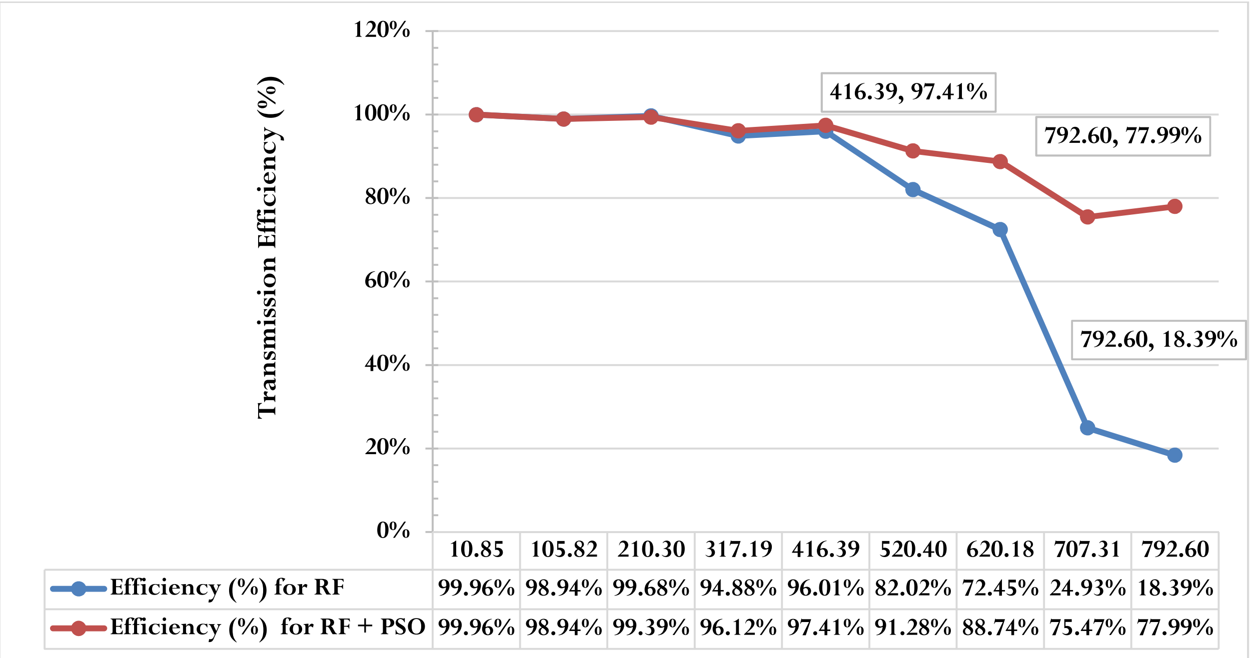
The packet time on air (ToA) achieved by the LoRa sensor when it transmits data packets over the given TD is given in Figure 4. The RF+PSO model maintained stable ToA in the range of 0.132 ms to 0.2 ms while the RF model ToA swings over a range of 0.372 ms to 0.02 ms.



	10.85	105.82	210.30	317.19	416.39	520.40	620.18	707.31	792.60	886.98
ToA (ms) for RF	0.1	0.372	0.02	0.157	0.065	0.138	0.123	0.176	0.137	0.215
ToA (ms) for RF + PSO	0.132	0.14	0.12	0.16	0.095	0.148	0.18	0.192	0.14	0.2

Figure 4 The packet time on air (ToA) achieved by the LoRa sensor when it transmits data packets over the given transmission distance (TD)

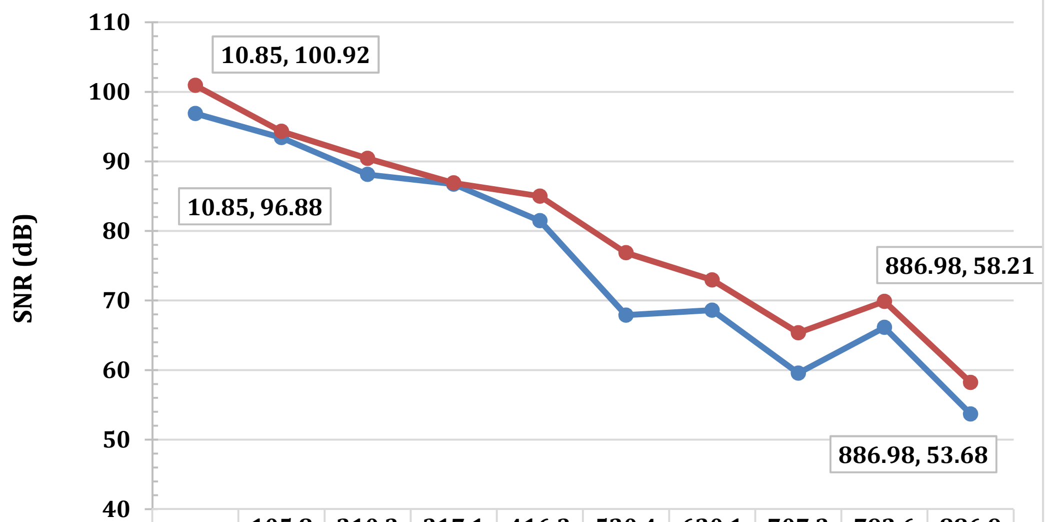
The transmission efficiency achieved by the LoRa sensor when it transmits data packets over the given TD is presented in Figure 5. The RF and the PSO enhanced RF model performed well at low TD with both models having transmission efficiency above 77 %. However, above TD of 416.39 m , the RF model performance dropped significantly reducing to a value of 18,39% at TD of 792.60 m whereas the RF + PSO model maintained high transmission efficiency that is above 77 % even at the TD of 792.60 m.



	10.85	105.82	210.30	317.19	416.39	520.40	620.18	707.31	792.60
Efficiency (%) for RF	99.96%	98.94%	99.68%	94.88%	96.01%	82.02%	72.45%	24.93%	18.39%
Efficiency (%) for RF + PSO	99.96%	98.94%	99.39%	96.12%	97.41%	91.28%	88.74%	75.47%	77.99%

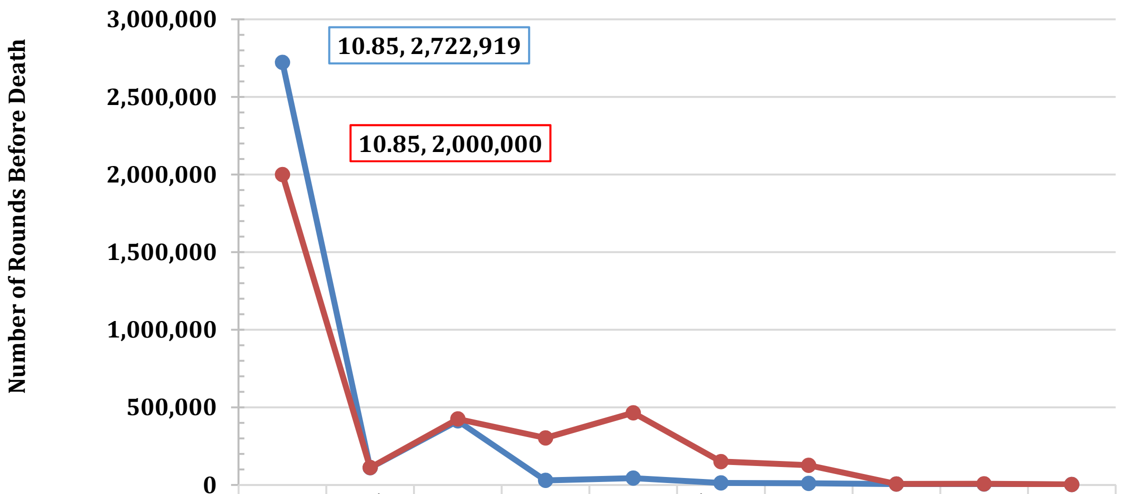
Figure 5 The transmission efficiency achieved by the LoRa sensor when it transmits data packets over the given transmission distance (TD)

The SNR achieved by the LoRa sensor when it transmits data packets over the given TD is presented in Figure 6. It shows that for both RF and RF + PSO models, the received signal SNR drops as TD increases. Also, the SNR values are in the range of 100.92 dB at TD value of 10.85 m to 58.21 dB at TD value of 886.98 m for the RF + PSO model whereas, the SNR values are in the range of 96.88 dB at TD value of 10.85 m to 53.68 dB at TD value of 886.98 m for the RF + PSO model. Essentially, the RF and RF + PSO model has better SNR performance at all the TD values than the RF baseline model.



	10.85	105.82	210.30	317.19	416.39	520.40	620.18	707.31	792.60	886.98
SNR (dB) for RF	96.88	93.41	88.12	86.72	81.46	67.89	68.6	59.55	66.13	53.68
SNR (dB) for RF + PSO	100.92	94.31	90.42	86.9	85	76.85	72.95	65.35	69.87	58.21

Figure 6 The SNR achieved by the LoRa sensor when it transmits data packets over the given transmission distance (TD)



	10.85	105.82	210.30	317.19	416.39	520.40	620.18	707.31	792.60	886.98
Rounds for RF	2,722,9	110,820	413,152	29,574	43,977	12,932	10,369	5,550	5,834	2,878
Rounds for RF + PSO	2,000,0	111,973	425,531	303,030	465,116	150,758	127,025	6,369	7,462	3,215

Figure 7 The number of rounds before death achieved by the LoRa sensor when it transmits data packets over the given transmission distance (TD)

The number of rounds before death achieved by the LoRa sensor when it transmits data packets over the given TD is presented in Figure 7. It shows that for the RF model performed bather than the RF + PSO model at the TD values less than 105.82 m. However, from TD of 105.82 m and above, the RF + PSO model performed better than the baseline model. Essentially, based on the number of rounds before death results, the baseline RF model can be recommended for TD values less than 105.82 m whereas the enhance RF+PSO model can be recommended for TD values above 105.82 m.

In any case, the number of rounds before death is not the only parameter to be considered when selecting the model to be employed. The overall results showed that the enhance RF+PSO model should be recommended for all TD.

4. Conclusion

In this work, two LoRa sensor energy consumption optimization model options are presented, namely; the Random Forest (RF) model baseline solution and the hybrid RF with particle swarm optimization (PSO) algorithm termed RF + PSO. The performance of the two options are evaluated at different transmission distances. The results showed that the enhance RF+PSO model maintained overall better performance than the baseline RF model. As such, the enhance RF+PSO model is recommended for LoRa sensor energy consumption optimization for all the TD values.

References

1. Kanoun, O., Bradai, S., Khriji, S., Bouattour, G., El Houssaini, D., Ben Ammar, M., ... & Viehweger, C. (2021). Energy-aware system design for autonomous wireless sensor nodes: A comprehensive review. *Sensors*, *21*(2), 548.
2. Khalifeh, A., Darabkh, K. A., Khasawneh, A. M., Alqaisieh, I., Salameh, M., AlAbdala, A., ... & Rajendiran, K. (2021). Wireless sensor networks for smart cities: Network design, implementation and performance evaluation. *Electronics*, *10*(2), 218.
3. BenSaleh, M. S., Saida, R., Kacem, Y. H., & Abid, M. (2020). Wireless sensor network design methodologies: A survey. *Journal of Sensors*, *2020*(1), 9592836.
4. Alaerjan, A. (2023). Towards sustainable distributed sensor networks: An approach for addressing power limitation issues in WSNs. *Sensors*, *23*(2), 975.
5. Keerthika, M., & Shanmugapriya, D. (2021). Wireless sensor networks: Active and passive attacks-vulnerabilities and countermeasures. *Global Transitions Proceedings*, *2*(2), 362-367.
6. Bathre, M., & Das, P. K. (2023). Smart dual battery management system for expanding lifespan of wireless sensor node. *International journal of communication systems*, *36*(3), e5389.
7. Qureshi, B., Aziz, S. A., Wang, X., Hawbani, A., Alsamhi, S. H., Qureshi, T., & Naji, A. (2022). A state-of-the-art survey on wireless rechargeable sensor networks: Perspectives and challenges. *Wireless Networks*, *28*(7), 3019-3043.
8. Al-Kaseem, B. R., Taha, Z. K., Abdulmajeed, S. W., & Al-Raweshidy, H. S. (2021). Optimized energy–efficient path planning strategy in WSN with multiple Mobile sinks. *IEEE Access*, *9*, 82833-82847.
9. Ehlali, S., & Sayah, A. (2022). Towards improved lifespan for wireless sensor networks: A review of energy harvesting technologies and strategies. *European Journal of Electrical Engineering and Computer Science*, *6*(1), 32-38.
10. Nkemeni, V., Mieyeville, F., Kuaban, G. S., Czekalski, P., Tokarz, K., Nsanyuy, W. B., ... & Zieliński, B. (2024). Evaluation of green strategies for prolonging the lifespan of linear wireless sensor networks. *Sensors*, *24*(21), 7024.
11. Bathre, M., & Das, P. K. (2020, July). Hybrid energy harvesting for maximizing lifespan and sustainability of wireless sensor networks: A comprehensive review & proposed systems. In *2020 international conference on computational intelligence for smart power system and sustainable energy (CISPSSE)* (pp. 1-6). IEEE.
12. Moltafet, M., Leinonen, M., Codreanu, M., & Pappas, N. (2021). Power minimization for age of information constrained dynamic control in wireless sensor networks. *IEEE Transactions on Communications*, *70*(1), 419-432.
13. Singh, A., Redhu, S., Beferull-Lozano, B., & Hegde, R. M. (2023). Network-aware RF-energy harvesting for designing energy efficient IoT networks. *Internet of Things*, *22*, 100770.
14. Ramalingam, S., & Baskaran, K. (2021). An efficient data prediction model using hybrid Harris Hawk Optimization with random forest algorithm in wireless sensor network. *Journal of Intelligent & Fuzzy Systems*, *40*(3), 5171-5195.