

Energy Efficient IoT-Sensors Network for Smart Farming

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Abstract- The experience of smart farming can be improved using IoT-based applications. Still, the performance of IoT networks may be degraded due to different factors, i.e., the coverage area of the farm/location (surface or underwater)/environmental conditions etc. Network operations over heterogeneous environments may cause excessive resource consumption and thus may reduce the IoT sensor's lifespan. To optimise energy consumption, in this paper, an energy-efficient method will be introduced for smart farming, and its performance will be analysed using different parameters (i.e., Throughput/energy consumption/residual energy etc.) using two different IoT standards (Long Range Low powered technology (LoRa)/SigFox).

Keywords- IoT, WSN, Agriculture, Energy, LoRa, SigFox .

I. INTRODUCTION

Smart farming deals with advanced solutions that can be implemented to increase overall production and operating costs can also be optimised. Internet of Things (IoT) based sensor network (IoT-WSN) can be deployed to achieve these goals that offer the following applications for smart farming as shown in figure 1:

- Air quality can be monitored to control the pollution level w.r.t crop health.
- Irrigation requirements can be estimated using historical data.
- Soil attributes can be calculated, and specific crops.
- Crop health/growth/disease can be analysed and controlled to avoid revenue loss.
- The amount of pesticide/fertiliser can be estimated to reduce the operational cost.
- As per weather conditions and forecasting, specific crop types can be selected for production to avoid future loss.

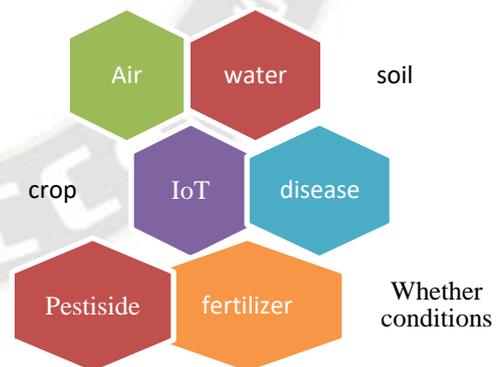


Figure: 1 Parameter measurement using IoT platform

IoT networks offer the following characteristics, as shown in Figure 2.

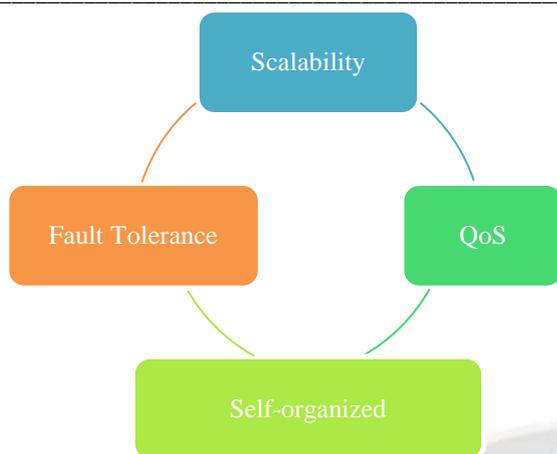


Figure 2: characteristics of IoT networks

- **Scalability:** IoT networks operate over a scalable environment and deal with heterogeneous devices and protocols. It is quite complex to exchange data between different platforms.
- **Fault Tolerance:** IoT networks can operate even after the breakdown of a few sensors.
- **Self-organised:** IoT sensors can initiate the routing operations automatically after deployment.
- **Quality of Service:** IoT networks can deliver the data under the constraints of quality-of-service parameters.

The following are the barriers to network operation in an agricultural environment:

- Transmission may be interrupted due to environmental conditions and internet availability, and its speed may affect the IoT network performance.
- The implementation cost of IoT sensors over farms is a major issue as it uses advanced hardware.
- IoT sensors operate in an open environment and thus may invite security threats.
- The accuracy of decision-making depends on the sensing accuracy of field sensors and thus may be reduced due to error-prone transmission.
- Excessive commutations may unnecessarily consume energy resources, another major concern for IoT networks.
- IoT sensors may consume more resources to process heterogeneous data processing and thus degrade network performance [1-5].

II. LITERATURE SURVEY

E. M. Ouafiq et al. [6] developed an energy-efficient solution to boost the network's lifetime. It offers optimal big data migration over Data Lake and supports prediction/forecasting using machine learning methods. It consumes less energy/computational resources in contrast to existing solutions.

P. K. Singh et al. [7] proposed a UAV-based IoT-enabled framework for smart farming that collects crop data under environmental constraints. An experimental study found that it can be used to maintain crop health/quantity of pesticides/fertiliser etc., using limited energy resources.

B. Miles et al. [8] developed an analytical model to estimate the optimal density of IoT sensors (over the coverage area of a farm) to maximise the network performance. Simulation-based outcomes indicate that it retains delivery ratio w.r.t. transmission range/duration etc.

A. D. Boursianis et al. [9] explored the role of WSN-IoT/UAV devices for smart farming applications. The study found that integration of these technologies can be used to provide different services (i.e. monitoring of crop health/disease types/phenotyping/ irrigation/weed etc.) as well as overall resource consumption/operational cost can be reduced using heterogeneous networks.

Gupta, Z., & Bindal, A. [10] argues that research institutions and scientific organisations have developed a promising technology in The Internet of Things (IoT) to address agricultural issues. This research examines how the Internet of Things is used in various agrarian settings.

L. Vijayaraja et al. [11] used a microcontroller with IoT sensors to collect the different factors related to soil/water/air etc. Experimental results indicate that the energy requirements of a network can be optimised using this solution, thus may minimise operational costs also.

L. Kaur et al. [12] explored the issues related to resource consumption over WSN-IoT networks w.r.t. smart farming. The study found that IoT sensors consume more energy under environmental constraints, and transmission can be interrupted due to these factors. It also found that routing strategies need to consider these constraints, and excessive resources may be consumed due to interruption/frequent retransmission etc. However, a fog computing platform can enhance energy consumption IoT routing protocols.

T. Khaoula et al. [13] deployed IoT sensors to monitor the various parameters (i.e. water level/quality/pollution etc.) for fish farming. It uses an artificial intelligence-based algorithm to manage these parameters. Outcomes show that it has minimal operational cost/energy consumption.

I. Ezzahoui et al. [14] studied IoT sensors' role in farming underwater plants/fish. These can be used to measure different parameters (i.e. plant's health/pesticide level/ toxicity/water temperature etc.) Analysis shows IoT sensors can be operated with minimal resource consumption and ensure product quality.

Gupta A. et al. [15] Clarify how the Internet of Things (IoT) can improve the communication capabilities of WSNs. However, the WSN-IoT concept presents new challenges for researchers and end users. Home, industry, healthcare, environment, and surveillance are just some domains this paper examines, along with related topics such as data acquisition/aggregation, optimal

energy consumption/harvesting for smart devices, scalable communication, etc.

A. Maroli et al. [16] highlighted the role of IoT-based applications over smart farming. Study shows that crop production can be enhanced using machine learning-based perdition and monitoring of various parameters (crop health/environmental conditions etc.) to ensure the quality of production and energy efficiency of IoT sensors can be optimised using intelligent algorithms.

P.Q. Huang et al. [17] investigated the issues related to resource consumption using IoT-based unmanned aerial vehicles (UAV). They presented a solution that builds multiple clusters to store the reference of trajectory traversal for UAV using the forms k-means clustering method. Experiments show that overall resource consumption can be optimised using this solution. However, it may vary w.r.t the flying path of the UAV.

J. Xu et al. [18] explored the various issues related to IoT-based agriculture. The study found that error-prone wireless channels and environmental conditions can degrade the quality of transmission as well as it is quite difficult to maintain the quality of collected data; usage of different hardware/software may increase the computational cost and data complexity, and there are no well-defined standards for data acquisition etc. All these are open issues, and the outcomes of this study can be used to develop solutions for the same.

A. Rejeb et al. [19] explored the role of IoT technology w.r.t. smart farming. The study found t that sensors may collect data from various entities (i.e. crop/soil attributes/animals/irrigation/weather etc.), and there is a need to define the standard for each subdomain. The study found a few other concerns related to data privacy/security and data migration over IoT networks, which are open issues.

Bhatt V et al. [20] In developing smart hardware for Industry 4.0, what opportunities and threats does the Internet of Things 4.0 present? The article examines high-tech tools for modern factories. It has cutting-edge capabilities like seamless interaction, data protection, human-machine interaction, hardware-software connectivity, and user-friendliness. Additionally, it examines big data for massive amounts of data, blockchain technology for secure data transmission, machine learning for data handling and analysis, and cloud computing for storage.

R. Akhter et al. [21] integrated the IoT network with the machine learning platform. They developed a solution to analyse the disease data, and this scheme can also predict the disease progression and its impact on crop health. Experiments show that it is a low-cost and highly efficient solution having minimal resource consumption, and it can be deployed over remote agricultural land located in hilly areas.

Y. Mona et al. [22] developed an energy-aware solution using thermoelectrically to extend the lifespan of IoT networks. Experiments indicate that it can operate in different

environmental conditions and is a low-cost solution that can be used to fulfil the energy requirements of IoT networks.

P.Q. Huang et al. [23] extended the scope of IoT networks by integrating the support of geographical routing with IoT platforms. Analysis shows that it can efficiently route the data to different locations, and outcomes show its optimal delay/resource consumption performance compared to existing geographical routing protocols.

K. S. S. Reddy et al. [24] developed an intelligent solution to optimise the resource consumption of IoT networks. It uses cross-layer data to analyse the modulation level w.r.t. energy requirement and predict the lifespan of sensors. Outcomes show that battery depletion depends on the data processing cycle, and regulating power drain can be minimised.

K Goel et al. [25] Precision agriculture has many advantages over conventional farming that should be discussed. There's talk of the wireless sensor network that measures soil moisture, temperature, and salinity. The concept of microbial fuel cell membranes, which use bacteria to produce acetate and accelerate the current for sensor batteries, is also discussed, along with deployment and communication techniques through the hybrid network. As a result, farmers will be able to raise their income and their crop yield.

D. Manikandan et al. [26] developed a cloud-based IoT solution for smart farming. It can predict the weather conditions to ensure uninterrupted transmission to the solar energy-driven base station. Experiments show that data transmission can be regulated using accurate forecasting.

A. I. Khan et al. [27] proposed a clustering algorithm for smart farming that can adapt optimal routing paths w.r.t. residual energy. Simulation-based analysis shows that it outperforms optimal energy consumption/delay/extended network lifetime etc.

M. S. Bali et al. [28] explored the role of green IoT and NB-IoT networks in the smart agriculture domain. The study found that these networks can easily resolve common issues (energy consumption/ connectivity/ efficient resource utilisation). The analytical data of this study can be further utilised to develop advanced solutions for smart farming.

D. Sarpal et al. [29] presented a machine learning algorithm that can predict crop production as per weather data to avoid revenue loss. Analysis shows that it is an energy-efficient solution that can be implemented to improve traditional farming techniques.

Goel, K et al. [30] In the context of precision agriculture using WSN, you should talk about how the dynamic computational overload and sensor density variations can affect the energy needed to run the network. Conventional energy harvesting schemes do not consider these conditions, which shortens the network's lifetime. To address the mentioned limitation, a regulated energy harvester will be introduced to WSN, and its performance will be evaluated using several performance metrics.

E. -T. Bouali et al. [33] presented a solution to manage renewable energy resources using IoT devices for smart farming. It uses a fuzzy-based method to regulate the water supply w.r.t. Irrigation requirements. Analysis shows that it offers optimal energy consumption/efficient usage of water resources for farming.

J. P. Rodríguez et al. [34] integrated an IoT platform with edge computing for smart farming. It uses a machine learning method for data classification to predict the production level over a certain period. Analysis indicates that it consumes fewer resources than traditional solutions and offers more services for end users (monitoring/prediction/operational cost optimisation). S. Piramuthu [35] reviewed the role of resource-constrained IoT-sensor networks for the food chain and supply management. The study found that energy-efficient IoT networks can be utilised to minimise the wastage of food/packaging material and thus may also reduce environmental pollution.

D. Jenzeri et al. [36] developed an IoT-enabled edge computing-based solution for smart farming. It can estimate the node deployment strategy over a large-scale coverage area to monitor multiple parameters simultaneously. Analysis shows that it is an energy-efficient solution that can enhance farming production and operational cost by analysing critical parameters for farmers.

M. C. Chiu et al. [37] developed an IoT-based solution to monitor the growth of fish w.r.t. feeding and water quality. A deep learning algorithm is used to classify the input dataset, and finally, predictions for fish feeding w.r.t. fish growth is made to ensure a higher production rate. Real-time implementation of this solution shows that it is a highly energy-efficient and low-cost solution for smart fish farming.

III. ENERGY EFFICIENT IOT-SENSOR NETWORK FOR SMART FARMING

IoT-WSN IoT Sensor network

Ie_lvl initial energy level

Vl_lvl voltage level

Txe_lvl Transmission energy level

Rxe_lvl Receiving energy level

Idl_e_lvl Idle energy level

Sl_e_lvl Sleep energy level

Bdp_lvl Battery depletion level

Bdp_rt Battery depletion rate

CPld Current Payload

$CPld = Packet_Size * Sampling\ Interval$

Pl Partial_load

$Pl = CPld / 2$

This paper introduces an energy-efficient scheme for IoT-WSN that can manage the packet transmission/retransmission w.r.t. current energy level. Flow chart 1 shows its basic steps, which are explained below:

Step 1: First, an IoT-WSN is initialised.

Step 2: Different energy levels are also initialised as given below:

Initial energy level: *Ie_lvl*

Voltage level: *Vl_lvl*

Transmission energy level: *Txe_lvl*

Receiving energy level: *Rxe_lvl*

Idle energy level: *Idl_e_lvl*

Sleep energy level: *Sl_e_lvl*

Battery depletion level: *Bdp_lvl*

Battery depletion rate: *Bdp_rt*

Step 3: Current depletion level and its rate is calculated as explained given below:

Bdp_rt Get depletion(){

$Bdp_rt_tx = active_interval_tx * Txe_lvl * recent(Vl_lvl)$

$Bdp_rt_rx = active_interval_rx * Rxe_lvl * recent(Vl_lvl)$

$Bdp_rt_idl = active_interval_idl * Idl_e_lvl * recent(Vl_lvl)$

$Bdp_rt_sle = active_interval_sle * Sl_e_lvl * recent(Vl_lvl)$

$Bdp_rt = Bdp_rt_tx + Bdp_rt_rx + Bdp_rt_idl + Bdp_rt_sle$

Return *Bdp_rt* }

Step 4: For normal transmission: calculate threshold energy to the allowed transmission

$Th_en_tx = Bdp_lvl / 2$

Step 5: In case of failure or payload reduction under re-constraints of threshold, packet re-transmission: is initiated, and threshold energy is calculated to allow re-transmission as given below:

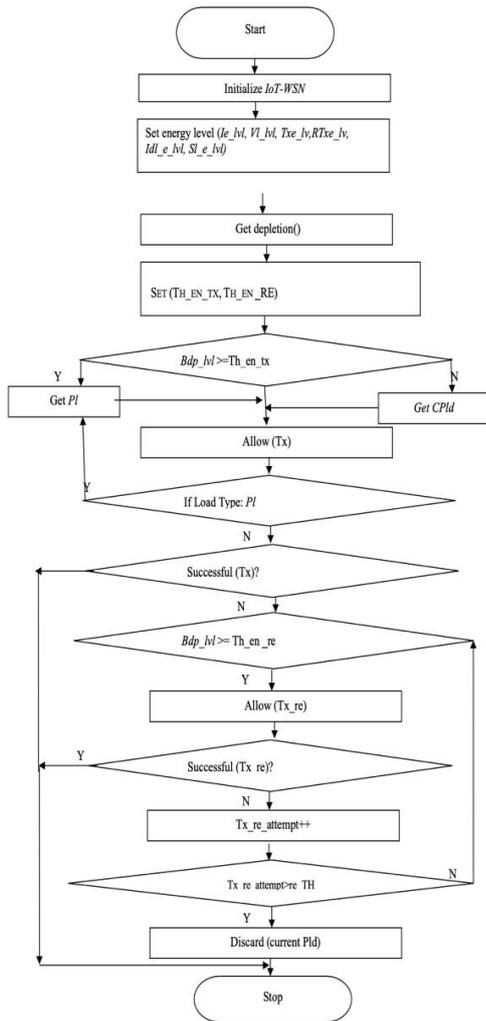
$TH_EN_RE = BDP_LVL / 4$

Step 6: First, the current battery depletion level is checked, and if it is higher than the threshold, transmission is allowed; otherwise current payload is reduced up to its half size. if $Bdp_lvl \geq Th_en_tx$, then allow (Tx) else $Pl / 2$

Step 7: Due to the above step, packet retransmission may occur due to packet loss or payload size reduction. The packet re-transmission threshold is calculated as per step 5; it is allowed only if THE battery depletion level is higher than THE threshold.

if $Bdp_lvl \geq Th_en_re$, then allow (reTx)

Step 8: After a few re-transmission attempts, transmission is discarded for that sensor w.r.t. current packet load.



Flow chart 1

IV. RESULTS AND ANALYSIS

For experiments, Network simulator-3 [31] was used with different parameters, i.e. Terrain Size is 5000*5000, the sampling interval is 10s, Packet Size is 50, and the initial energy is 26.5 J. Rx/Tx (10) Simulation Time is 4000 Seconds, IoT Sensor Density varies from 100-400 nodes, Platform is Linux, and IoT Standard is LoRA. Different simulation scenarios are IoT sensor networks without an energy-efficient scheme (IoT-NES) and IoT sensor networks with an energy-efficient system (IoT-WES) using different IoT standards (LoRa/SigFox).

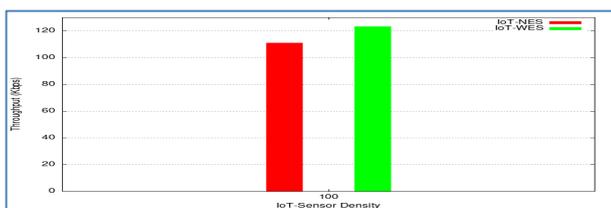


Figure: 3 Throughput-IoT-Sensors-100-LoRa

Figure: 3 shows the Throughput with IoT-Sensors-100 with different scenarios, i.e. IoT-NES and IoT-WES. In the case of

IoT-NES, it is 111 Kbps, whereas it is slightly higher with IoT-WES (123 Kbps).

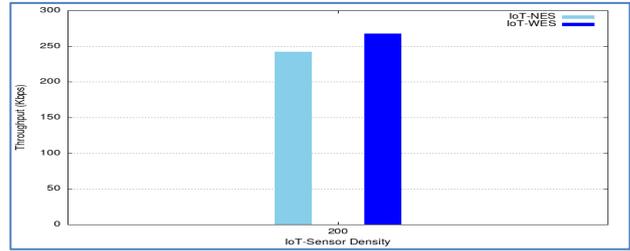


Figure: 4 Throughput-IoT-Sensors-200-LoRa

Figure: 4 shows the Throughput with IoT-Sensors-200 with different scenarios, i.e. IoT-NES and IoT-WES. In the case of IoT-NES, it is 242 Kbps, whereas it is slightly higher with IoT-WES (268 Kbps).

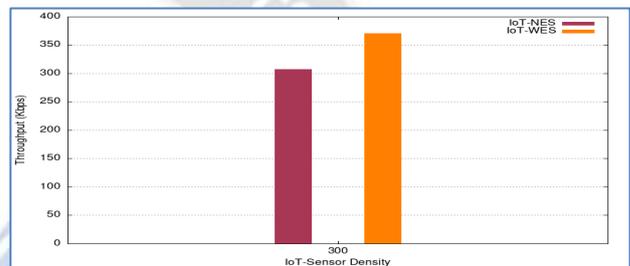


Figure: 5 Throughput-IoT-Sensors-300-LoRa

Figure: 5 shows the Throughput with IoT-Sensors-300 with different scenarios, i.e. IoT-NES and IoT-WES. In the case of IoT-NES, it is 307 Kbps, whereas it is slightly higher with IoT-WES (371 Kbps).

Figure: 6 shows the Throughput with IoT-Sensors-400 with different scenarios, i.e. IoT-NES and IoT-WES. In the case of IoT-NES, it is 417 Kbps, whereas it is slightly higher with IoT-WES (540 Kbps).

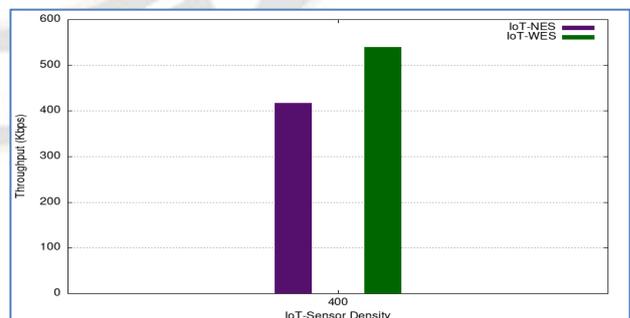


Figure: 6 Throughput-IoT-Sensors-400-LoRa

Figure 7 compares the throughput of IoT-NES/IoT-WES scenarios w.r.t. IoT Sensors density (100-400). It can be observed that with 100 IoT sensors, both methods (IoT-NES/IoT/WES) delivered marginal throughput. As the sensor density increases to 200 to 300, it is average and researches to

its peak value with the highest sensor density (400). Analysis shows that IoT-WES delivered better throughput under the constraints of sensor density variations than IoT-NES.

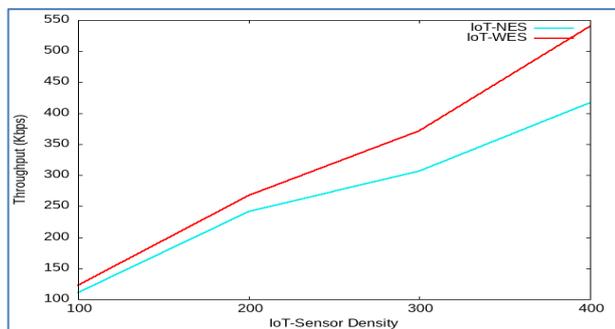


Figure: 7 Comparison-Throughput -IoT-Sensors-(100-400) - LoRa

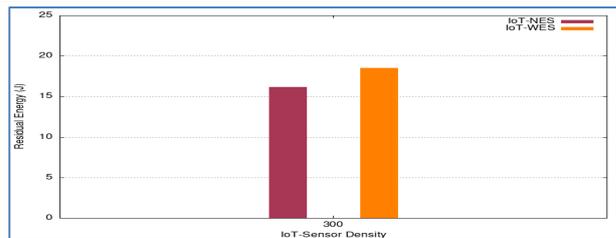


Figure: 10 Residual Energy-IoT-Sensors-300-LoRa

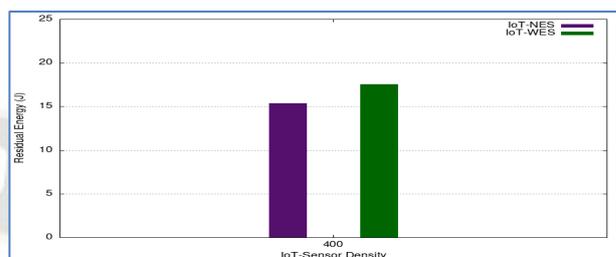


Figure: 11 Residual Energy-IoT-Sensors-400-LoRa

Figure: 11 shows the Residual Energy with IoT-Sensors-400 with different scenarios, i.e. IoT-NES and IoT-WES. In the case of IoT-NES, it is 15.388 J, whereas it is slightly higher with IoT-WES (17.5355 J).

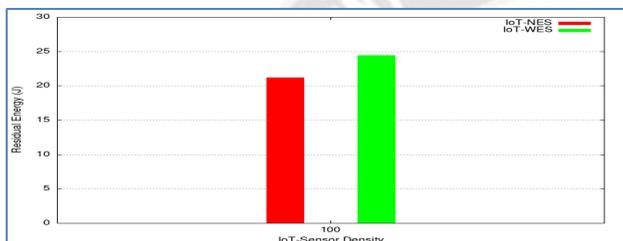


Figure: 8 Residual Energy-IoT-Sensors-100-LoRa

Figure: 8 shows the Residual Energy with IoT-Sensors-100 with different scenarios, i.e. IoT-NES and IoT-WES. In the case of IoT-NES, it is 21.2087 J, whereas it is slightly higher with IoT-WES (24.4291 J).

Figure 12 compares the residual energy of IoT-NES/IoT-WES scenarios w.r.t. IoT Sensors density (100-400). It can be observed that In the case of 100 IoT sensors, it is higher for both scenarios (IoT-NES/IoT-WES). As IoT sensor density increased from 200 to 300, there was a sharp decline in its level, and for the peak IoT sensor density, it reached its minimum value.

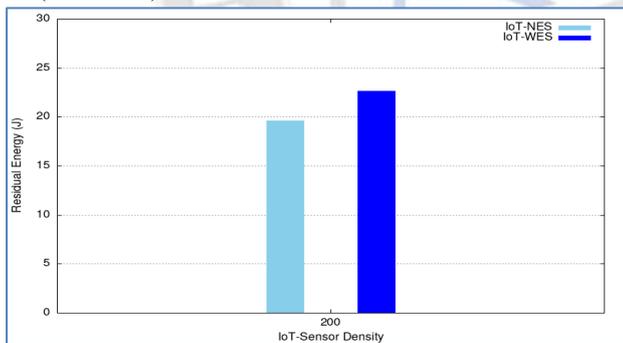


Figure: 9 Residual Energy-IoT-Sensors-200-LoRa

Figure: 9 shows the Residual Energy with IoT-Sensors-200 with different scenarios, i.e. IoT-NES and IoT-WES. In the case of IoT-NES, it is 19.6261 J, whereas it is slightly higher with IoT-WES (22.6313 J).

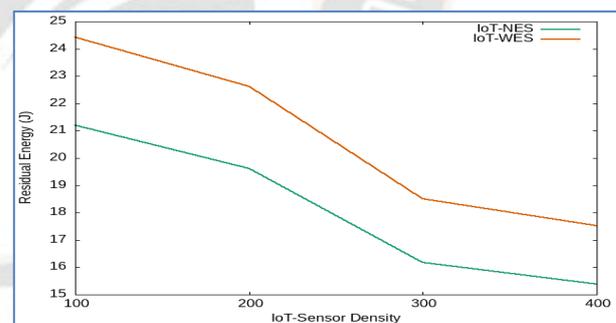


Figure: 12 Comparison-Residual Energy-IoT-Sensors-(100-400) -LoRa

As per the analysis, IoT-WES tried to maintain a higher residual energy level in contrast to IoT-NES under the constraints of IoT sensor density.

Figure: 10 shows the Residual Energy with IoT-Sensors-300 with different scenarios, i.e. IoT-NES and IoT-WES. In the case of IoT-NES, it is 16.1888 J, whereas it is slightly higher with IoT-WES (18.4985 J).

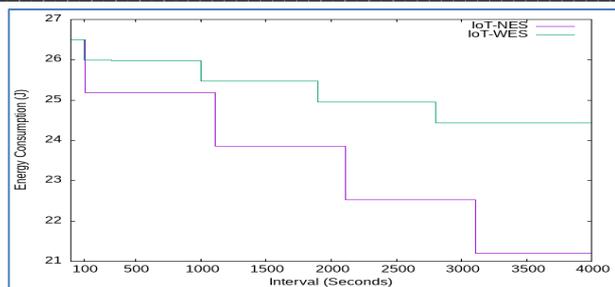


Figure: 13 Energy Consumption of IoT-NES and IoT-WES- with IoT-Sensors-100-LoRa

Figure: 13 shows the energy consumption of IoT-NES and IoT-WES with 100 IoT sensors. It can be observed that the energy consumption of IoT-NES is quite higher as compared to IoT-WES over the given interval (100 s to 4000 s).

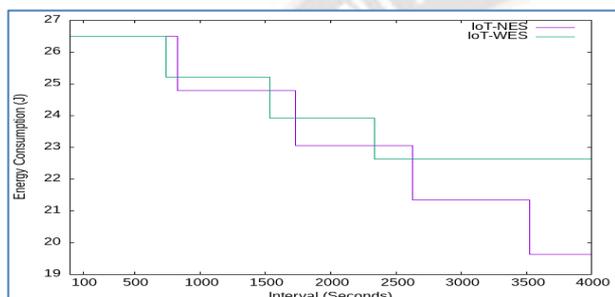


Figure: 14 Energy Consumption of IoT-NES and IoT-WES- with IoT-Sensors-200-LoRa

Figure 14 shows the energy consumption of IoT-NES and IoT-WES with 200 IoT sensors. It can be observed that the energy consumption of IoT-NES is quite higher as compared to IoT-WES over the given interval (100 s to 4000 s). IoT-WES maintained consistent energy levels till the end of the simulation as compared to IoT-NES.

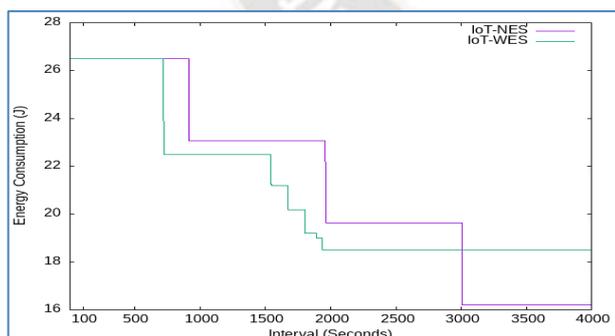


Figure: 15 Energy Consumption of IoT-NES and IoT-WES- with IoT-Sensors-300-LoRa

Figure: 15 shows the energy consumption of IoT-NES and IoT-WES with 300 IoT sensors. It can be observed that the energy consumption of IoT-NES is quite higher as compared to IoT-WES over the given interval (100 s to 4000 s). However, there is a sharp decline in energy levels using IoT-WES compared to IoT-NES.

Figure: 16 shows the energy consumption of IoT-NES and IoT-WES with 400 IoT sensors. It can be observed that the energy consumption of IoT-NES is quite higher as compared to IoT-WES over the given interval (100 s to 4000 s).

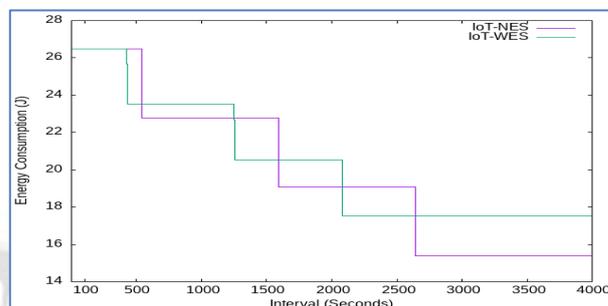


Figure: 16 Energy Consumption of IoT-NES and IoT-WES- with IoT-Sensors-400-LoRa

Performance analysis of SigFox using IoT-NES/IoT-WES

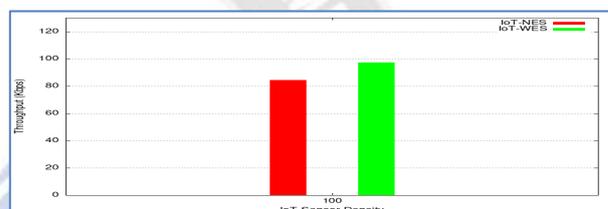


Figure: 17 Throughput-IoT-Sensors-100-SigFox

Figure: 17 shows the Throughput of different scenarios, i.e. IoT-NES and IoT-WES, using SigFox with 100 sensors. In the case of IoT-NES, it is 84.324324 Kbps, whereas it is slightly improved with IoT-WES (97.196262 Kbps).

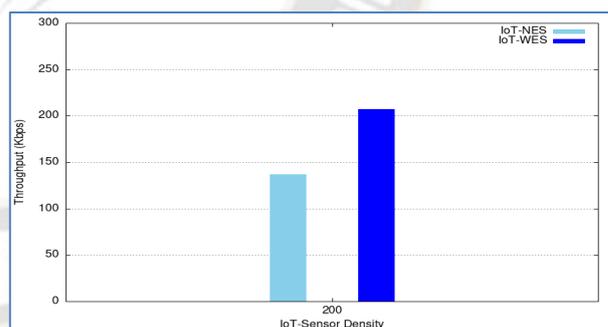


Figure: 18 Throughput -IoT-Sensors-100-SigFox

Figure: 18 shows the Throughput of different scenarios, i.e. IoT-NES and IoT-WES, using SigFox with 200 sensors. In the case of IoT-NES, it is 136.901408 Kbps, with 206.808511 Kbps using IoT-WES.

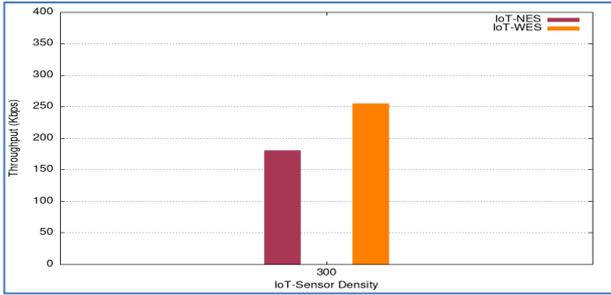


Figure: 19 Throughput -IoT-Sensors-300-SigFox

Figure: 19 shows the Throughput of different scenarios, i.e. IoT-NES and IoT-WES, using SigFox with 300 sensors. In the case of IoT-NES, it is 180.759494 Kbps, with 254.772525 Kbps using IoT-WES.

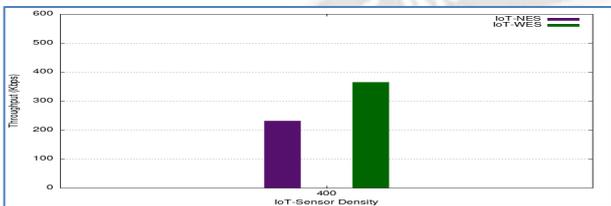


Figure: 20 Throughput -IoT-Sensors-400-SigFox

Figure: 20 shows the Throughput of different scenarios, i.e. IoT-NES and IoT-WES, using SigFox with 400 sensors. In the case of IoT-NES, it is 230.9677424 Kbps, with 364.067797 Kbps using IoT-WES.

Figure 21 compares the throughput of IoT-NES/IoT-WES scenarios w.r.t. IoT Sensors density (100-400) using SigFox standard. It can be observed that with minimal sensors (100) in both a method (IoT-NES/IoT/WES), there is marginal throughput.

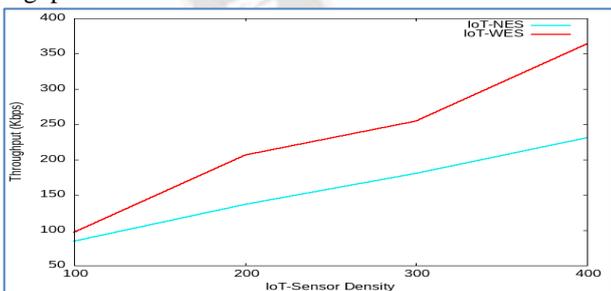


Figure: 21 Throughput- comparison IoT-Sensors-100-400-SigFox

As the sensor density increases, it also varies and is highest with maximum sensor density (400). However, it goes using IoT-WES w.r.t. sensor density. Analysis shows that IoT-WES improved the overall throughput.

Figure: 22 shows the Residual Energy of SigFox with 100 IoT Sensors with different scenarios, i.e. IoT-NES and IoT-WES. In the case of IoT-NES, it is 18.5 J, whereas it is slightly higher with IoT-WES (20.1 J).

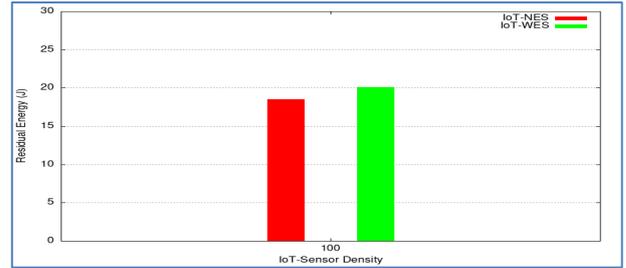


Figure: 22 Residual Energy-IoT-Sensors-100-SigFox

Figure: 23 shows the Residual Energy of SigFox with 200 IoT Sensors with different scenarios, i.e. IoT-NES and IoT-WES. In the case of IoT-NES, it is 16.9 J, whereas it is 17.7 J with IoT-WES.

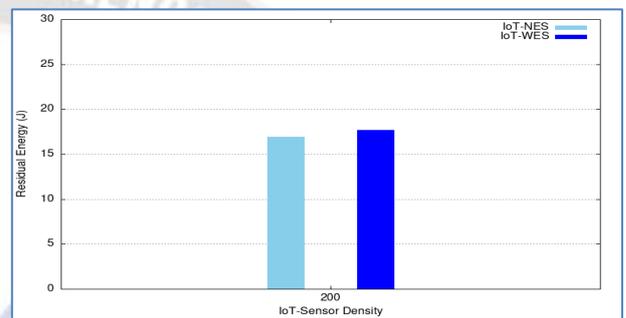


Figure: 23 Residual Energy-IoT-Sensors-200-SigFox

Figure: 24 shows the Residual Energy of SigFox with 300 IoT Sensors with different scenarios, i.e. IoT-NES and IoT-WES. In the case of IoT-NES, it is 14.5 J, whereas it is 15.3 J with IoT-WES.

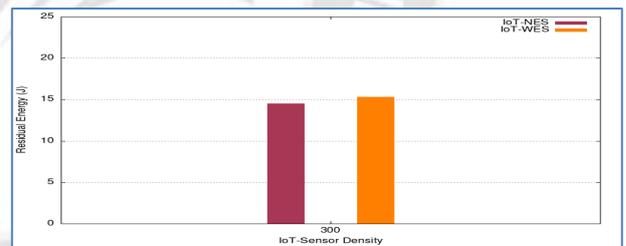


Figure: 24 Residual Energy-IoT-Sensors-300-SigFox

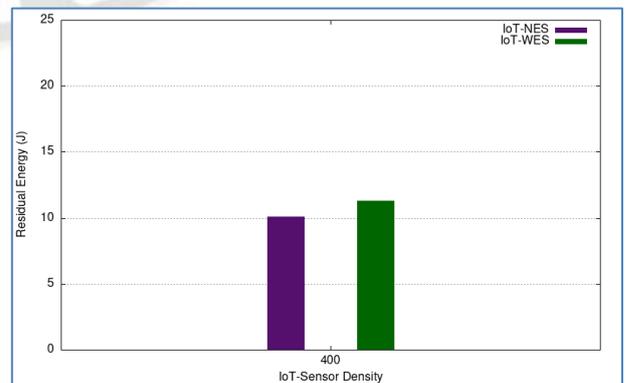


Figure: 25 Residual Energy-IoT-Sensors-400-SigFox

Figure: 25 shows the Residual Energy of SigFox with 400 IoT Sensors with different scenarios, i.e. IoT-NES and IoT-WES. In IoT-NES, it is 10.1 J, whereas it is 11.3 J with IoT-WES.

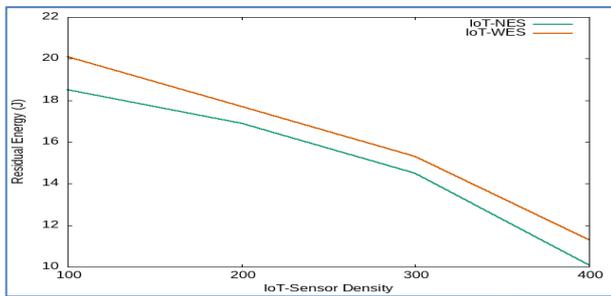


Figure: 26 Comparison-Residual Energy-IoT-Sensors-(100-400)

Figure 26 compares residual energy of IoT-NES/IoT-WES scenarios w.r.t. IoT Sensors density (100-400) using SigFox. It can be observed that with minimal sensor density (100), it is highest for both IoT-NES/IoT-WES, and there is a sharp decline in its value as the sensor density increases from 200 to 400 sensors. It reaches its minimum value with peak sensor density (400). However, IoT-WES retained its acceptable level in contrast to IoT-NES.

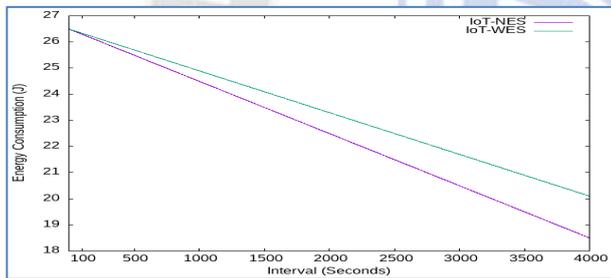


Figure: 27 Energy Consumption of IoT-NES and IoT-WES with IoT-Sensors-100-SigFox

Figure: 27 shows the energy consumption of IoT-NES and IoT-WES with 100 IoT sensors using SigFox. It can be observed that the energy consumption of IoT-NES is quite higher as compared to IoT-WES over the given interval (100 s to 4000 s), and IoT-NES could not retain its residual energy. There is a sharp decline in its value as compared to IoT-WES.

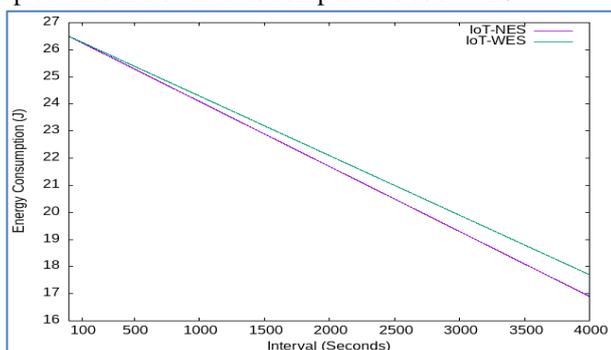


Figure: 28 Energy Consumption of IoT-NES and IoT-WES with IoT-Sensors-200-SigFox

Figure: 28 shows the energy consumption of IoT-NES and IoT-WES with 200 IoT sensors using SigFox. It can be observed that the energy consumption of IoT-NES and IoT-WES is minimal at the starting of the simulation, and IoT-NES consumed higher energy as compared to IoT-WES. There is a gradual decline in its residual energy as compared to IoT-WES.

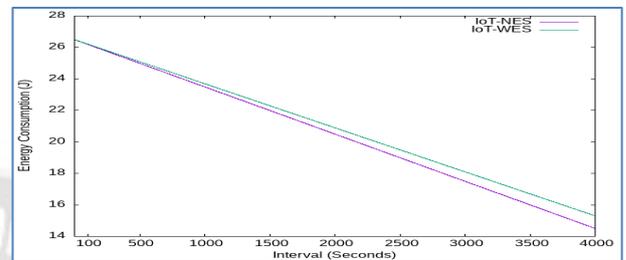


Figure: 29 Energy Consumption of IoT-NES and IoT-WES with IoT-Sensors-300-SigFox

Figure: 29 shows the energy consumption of IoT-NES and IoT-WES with 300 IoT sensors using SigFox. Results show that IoT-NES consumed more energy, and its residual energy is less than IoT-WES until the end of the simulation interval.

Figure: 30 shows the energy consumption of IoT-NES and IoT-WES with 400 IoT sensors using SigFox. It can be analysed that IoT-NES consumed higher energy with peak sensor density and could not retain its residual energy level compared to IoT-WES. Performance comparison of LoRa and SigFox using IoT-NES and IoT-WES.

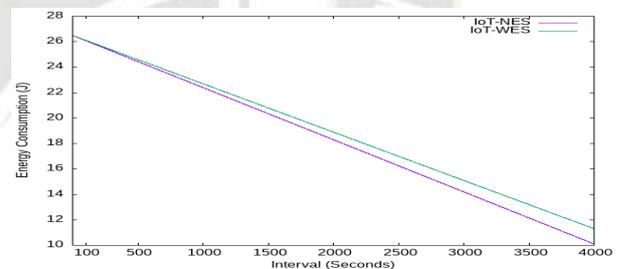


Figure: 30 Energy Consumption of IoT-NES and IoT-WES with IoT-Sensors-400-SigFox

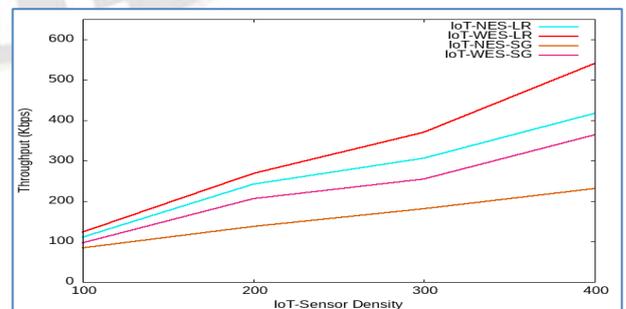


Figure: 31 Throughput-comparison-LoRa/SigFox

Figure 31 shows the throughput comparison of LoRa (LR) and SigFox (SG) IoT standards. It can be analysed that IoT-NES has

less throughput using SigFox than LoRa. Using IoT-WES, it was improved for both measures.

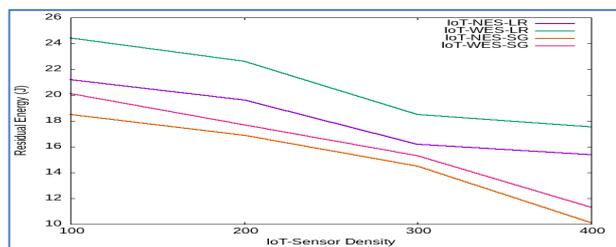


Figure: 32 Residual Energy-comparison-LoRa/SigFox

Figure 32 shows the residual energy comparison of LoRa and SigFox IoT standards. It indicates that IoT-NES consumed higher energy using LoRa and SigFox and is further optimised using IoT-WES for LoRa/SigFox. It also shows that IoT-WES is more compatible with LoRa than SigFox.

V. CONCLUSION

This paper presented an energy-efficient scheme over an IoT platform for smart farming using LoRa and SigFox IoT communication standards. Their performance was also analysed under different constraints (i.e., throughput/residual energy/energy consumption etc.) by varying the density of IoT sensors. In the case of IoT-NES, the network delivered the average Throughput with the IoT-sensor density (100-400).

It can also be observed that by varying the sensor density, Throughput can be enhanced over the cost of resource consumption. Using LoRa, in the case of IoT-WES, the network delivered the higher Throughput with the IoT-sensor density (100-400) and varied w.r.t. sensor density. It can be analysed that with medium sensor density (100-200), there is a marginal improvement in Throughput, whereas, with sensor density (300-400), IoT-WES tried to improve it significantly.

In the case of residual energy, IoT-NES retained the highest energy level with minimal sensor density; however, under the constraint of the scalable network, it could not manage the energy consumption and consumed the highest energy with peak sensor density (400). For IoT-WES, it declined gradually w.r.t. sensor density.

It also offered the highest energy level with minimal sensor density. As the sensor density varies up to 400, it also consumes higher energy, thus reducing the overall level of residual energy. In the case of energy consumption over the interval, it can be analysed that w.r.t. sensor density variations it varies for both IoT-NES and IoT-WES scenarios. Each scenario gradually decreases for medium-level sensor density (100-200), but more energy was consumed for higher sensor density (200-400). However, IoT-WES retained its level till the end of the simulation interval. Using SigFox, with IoT-NES, the network offered average Throughput under the sensor density constraints compared to LoRa.

However, there is little improvement as the sensor density increases to 400, but still, it is less than LoRa. The residual energy of IoT-NES remains higher with minimal sensor density and is steadily declining under the constraints of the scalable network compared to IoT-WES. IoT-NES consumed more power and reduced the overall network lifespan, further recovered using IoT-WES. As per the above discussion, it can be concluded that IoT-WES has higher Throughput with optimal residual energy level and acceptable energy consumption under the constraints of the salable network compared to IoT-NES. It can also be observed that IoT-WES can be used with LoRa to improve network efficiency and is less compatible with SigFox. Currently, it is developed to work only over IoT sensor networks using LoRa and SigFox standards. There is a need to improve the performance of IoT-WES using SigFox also. Its implementation will be analysed over other networks (i.e., vehicular area networks/mobile ad hoc networks).

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