Energy harvesting based data incorporated management model for Internet of Things School of Computer Science Engineering and Information Systems Vellore Institute of Technology Vellore

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ABSTRACT

The IoT represents a much wider network of interrelated devices, all the time being fed by data generation and transmission. However, to this day, this remains a considerable problem to manage energy consumption by the devices as such in distant or energy-scarce environments. This paper proposes an Energy-Harvesting-Based Data Management Model, wherein the energy use in IoT devices is optimized through harnessing renewable energy sources such as solar light energy and kinetic energy. The model incorporates the so-called adaptive algorithms and improved data routing techniques-with these meant to maximize energy efficiency-maintaining at the same time the smooth operation of data management even in the energy-defaulting states. Simulation results using the Cisco Packet Tracer demonstrate how the model effectively manages energy, prolongs device life, and allows continuous process execution in the IoT.[1] This solution is greatly of benefit for deployment in remote and difficult-to-manage environments of an IoT setting and will ensure that energy consumption in data transmission is sustainable.

KEYWORDS: Internet of Things, energy harvesting, data management, IoT devices, Cisco Packet Tracer, renewable energy, adaptive algorithms, network optimization..

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INTRODUCTION

The Internet of Things (IoT) has experienced a rapid growth in which billions of devices are connected to the internet, allowing them to perform tasks ranging from environmental monitoring to smart city management. The proliferation of these devices raises one significant issue: power consumption.[2] Many IoT devices run on batteries, which are sometimes difficult to replace or recharge, especially in remote or harsh environments. Thus arises the need for energy-efficient designs that can ensure continuous operation of IoT devices without absolute maintenance.

Energy harvesting is a promising technique that allows the IoT system to tap energy from different sources around them, such as solar, kinetic, or thermal energy. Incorporation of such renewable energy sources into IoT systems decreases the traditional battery reliance, thus prolonging life and minimizing costs for operational IoT.

However, energy harvesting for supplying power is proving to be one of the solutions to complex problems. Data- and energy-management could be rather tedious and complicated in a disruptive environment of IoT. Balancing the energy made available with the data transmission requirement is vital to ensure non-interruption in the functioning of devices. Herein, we propose an energy-harvesting-based data management model, where intelligent data routing and adaptive energy management algorithms are combined for solving these issues.[3]

ARCHITECTURE DIAGRAM

This architecture is built up of the following basics:

The energy is harnessed in the Energy Harvesting Layer. Inputs such as solar panels or IoT sensor inputs attached to kinetic devices are used to capture electricity for power. In the upper layer, it has the Data Management Layer that filters data for scheduled tasks and decides enough energy for optimal processing. The Communication Layer is at the bottom layer, acting as a bridge between hardware devices and cloud or on-site servers, maintaining networking and supporting IoT functions without a break in connectivity.

(A conceptual architecture diagram would show IoT devices attached to energy harvesting sources; the processing and network elements of the diagram would fit in.)[4]

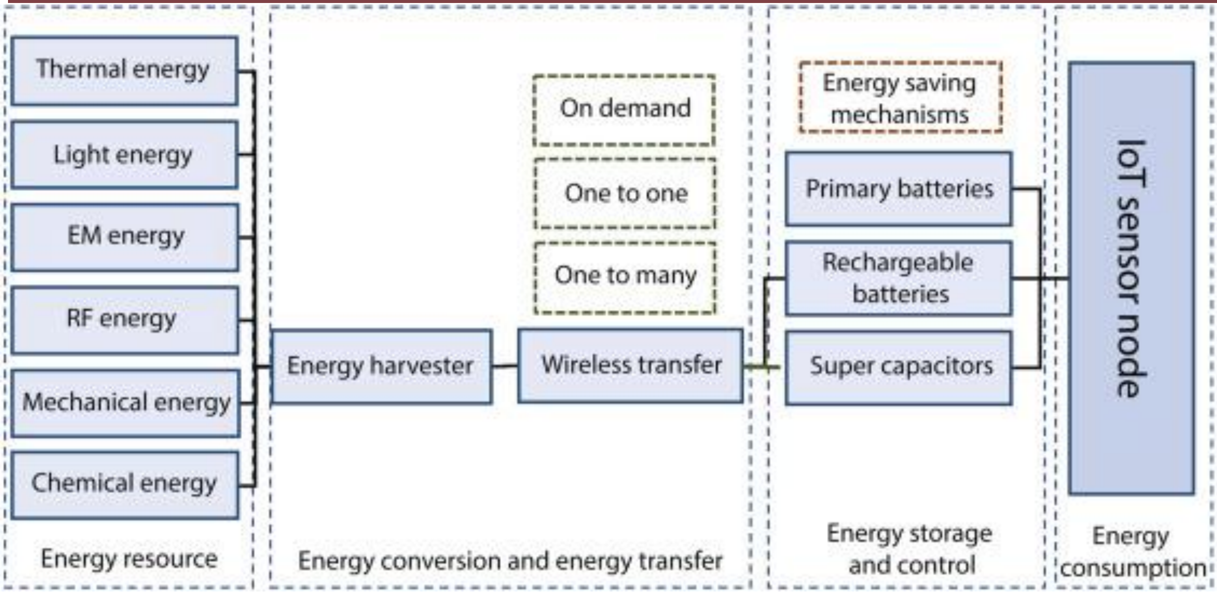

Figure 1. Architectural diagram with IoT devices

METHODOLOGY

The integrated model supports data management and energy efficiency by three key components: Energy Harvesting Unit captures energy from environmental sources such as solar panels or piezoelectric devices and stores it in a buffer before being distributed to IoT devices for continuous operation. Adaptive Data Management Algorithm will optimize energy consumption while working. The algorithm shall realize the fact that for periods during which it happens to garner enough energy, its rates in data collection as well as data transmission could also be set high, during low periods of energy accumulation, there will be putting off unimportant tasks such as transmitting data and reducing the bits to transmit via nodes perceived to hold minor or of no significance whatsoever to them. Network And Communication utilized energy aware protocol for network topology because every node passed on the transmitted data plus balanced out each other loads. The environment is a simulated communication network using Cisco Packet Tracer; hence, we can assess the energy-efficient routing protocols in real applications of IoT.[5][6]

NETWORK DESIGN AND DIAGRAM

The digital network adapter is set up in Cisco Packet Tracer to provide an integrated network system, whereby IoT devices interconnect with routers to a central data hub or to cloud servers. Essential energy harvesting nodes are dispersed throughout the network all aimed at sufficiently supplying power to critical areas.[7]
(Will include a network diagram showing the communication between routers, energy harvesting units, and IoT devices and show the flow of both data and energy across networked devices.)

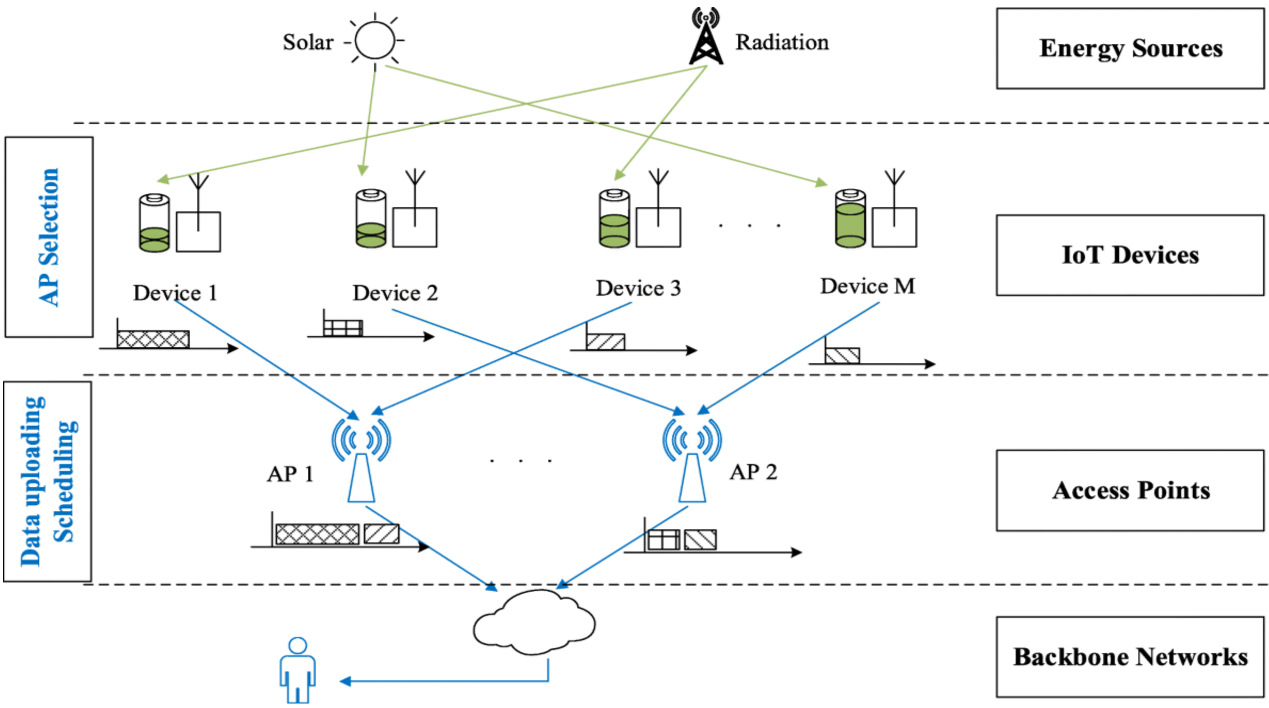

Figure 2. IoT devices communicate with routers.

FORMULA AND ALGORITHMS

Here's the corrected and structured version of the transmission delay formula under the federated learning system:

TRANSMISSION DELAY

OFDMA, which remains the strongest reference toward future 6G wireless networks, is used for uplink transmission in the considered federated learning system. Suppose there are M resource blocks in the uplink forming resource block set Ω. During the training round t, the ith device sends its local federated learning model parameters to the base station through resource block n. The uplink rate for this transmission is given in Equation (1)

$$c_{i,n,t}^{\mathrm{Up}} = B^{\mathrm{Up}} \log\left(1 + \frac{P_{i,t} h_i}{I_n + B^{\mathrm{Up}} N_0}\right)$$

where:

- B^{Up} is the bandwidth of a single resource block in the uplink,
- $P_{i,t}$ is the transmission power of device i during round t,
- I_n is the interference on resource block n,
- N_0 is the noise power spectral density,
- h_i is the channel gain from device iii to the server.

Based on the resource block matching scheme, the total uplink rate for device i during round t is expressed by Equation (2):

$$c_{i,t}^{\mathrm{Up}} = \sum_{n=1}^{M} r_{i,n,t} c_{i,n,t}^{\mathrm{Up}}$$

where,

$r_{i,n,t} \in \{0,1\}$ in $r_{i,n,t} = 1$ use resource block *n* for parameter transmission in round *t* training of device *i*.

$r_{i,n,t} = 0$ on the contrary, do not use resource block *n* for parameter transmission.

The uplink transmission delay of the *t*-round training of the corresponding device i through the resource block *n* is expressed in Eq.(3):

$$T_{i,n,t}^{\mathrm{Up}} = \frac{D}{c_{i,n,t}^{\mathrm{Up}}}$$

The transmission delay of the *t*-round training of device i is expressed in Eq. (4):

$$T_{i,t}^{\mathrm{Up}} = \sum_{n=1}^{M} r_{i,n,t} T_{i,n,t}^{\mathrm{Up}}$$

The corresponding downlink delay is expressed Eq.(5):

$$T^{\mathrm{Down}} = \frac{D}{c^{\mathrm{Down}}}$$

The device trains the local model locally using its computing resources. The calculation delay of the *t*-round training of device *i* is expressed in Eq. (6):

$$T_{i,t}^{\mathrm{Comp}} = \frac{\varepsilon_i K_i \varpi_i}{f_{i,t}}$$

where,

ε_i, K_i and ϖ_i the sizes of the sample data of device *i*, the number of samples of the device, and the number of CPU cycles required to process each bit of data respectively

$f_{i,t}$ is the CPU frequency of the t-th round of training for device i.

Combining the three delays, the delay of the t-th round of training for device *i* is expressed in Eq. (7):

$$T_{i,t} = T_{i,t}^{\mathrm{Up}} + T_{i,t}^{\mathrm{Comp}} + T^{\mathrm{Down}}$$

The training delay of each round of federated learning depends on the maximum delay of the selected device, so the delay of the t-th round of training is expressed in Eq.(8):

$$T_t = \max_{i \in A_t}\left(T_{i,t}^{\mathrm{Up}} + T_{i,t}^{\mathrm{Comp}}\right) + T^{\mathrm{Down}}$$

ENERGY LOSS

In this case, hence coming into the assumption that the power supply to all node servers is sufficiently large, the energy consumption incurred on the server is neglected altogether. The focus is really on the energy consumed on the client devices. The energy consumption incurred by each device can be broadly categorized into two parts: energy consumption for local training and energy consumption during wireless transmission. Therefore, for all intents and purposes, total energy consumption by the device i in round t is expressed by the equation.

$$e_{i,t} = \delta_i \overline{\omega}_i f_{i,t}^2 \varepsilon_i K_i + P_{i,t} T_{i,t}^{\mathrm{Up}}$$

where:

- $\delta_i \overline{\omega}_i f_{i,t}^2 \varepsilon_i K_i$ represents the energy consumption of device i during the t-th round of local model training. It depends on:
  - δ_i : the energy consumption coefficient of the processor of device i,
  - $\overline{\omega}_i$: the number of CPU cycles required per bit of data,
  - $f_{i,t}$: the CPU frequency of device i in round t,
  - ε_i : the size of the sample data of device i.
- $P_{i,t} T_{i,t}^{\mathrm{Up}}$ represents the energy consumption for uplink wireless transmission, where:
  - $P_{i,t}$ is the transmission power of device i in round t,
  - $T_{i,t}^{\mathrm{Up}}$ is the uplink transmission delay for device i.

TRANSMISSION SUCCESS PROBABILITY

These transmission errors can occur as a result of interference and noise in the wireless channel. The average packet error rate (PER) of a data transmission system over quasi-static fading channels is provided. When a certain condition of the wireless channel is reached, the first threshold known as a waterfall threshold is reached. To either induce or not induce an error on resource block n for device iii during the t-th round of training is illustrated by Equation (3):

$$\mathrm{Error}_{i,n,t} = 1 - e^{\left(\frac{-m\left(I_n + B^{\mathrm{Up}} N_0\right)}{P_{i,t} h_t}\right)}$$

where:

- $P_{i,t} h_i / I_n + B^{\mathrm{Up}} N_0$: The signal-to-interference-plus-noise ratio (SINR) on resource block n,
- m : Waterfall threshold, which indicates the minimum signal strength required for reliable communication.
- P_i : Transmission power of device i, representing the power used by device i to send its signal.
- h_i : Channel gain for device i, which quantifies how much the signal strength is affected by the transmission medium and distance.
- I_n : Interference on resource block n, representing the total interference experienced by device i on the specific resource block n.
- B^{Up} : Uplink bandwidth, the range of frequencies available for devices to transmit their signals to a base station.
- N_0 : Noise power spectral density, which indicates the power of noise per unit bandwidth in the system.

Assuming that the local model is transmitted in a single packet and that transmission failures are not retransmitted, the success probability of device iii transmitting the local model using resource block i in round t is given by Equation (4):

$$q_{i,n,t} = e^{\left(\frac{-m\left(I_n + B^{\mathrm{Up}} N_0\right)}{P_{i,t} h_i}\right)}$$

Finally, the overall success probability of device i successfully completing the training and transmission of its local model in round t is represented as:

$$q_{i,t} = \sum_{n=1}^{R} r_{i,n,t} q_{i,n,t}.$$

PROPOSED ALGORITHM

The proposed algorithm decouples P2 into three sub-problems: device resource allocation, communication resource allocation, and battery energy allocation that can be iteratively optimized.

The transmission power and CPU frequency of the device are to be optimized in order to achieve the target energy expenditure for maximizing the learning efficiency, but this optimization subproblem is NP-hard, thus an approximate solution for the device resource allocation is provided. The reduction of global loss as a function of the transmission success rate is approximately non-linear and independent of the CPU frequency. In a best-case scenario, the impact of the transmission change moment on the attenuation will hardly change. The minimization of delay is meant to take the counterpoint from the point of maximization, which is the point of minimizing learning efficacy, as compared to delay, since the delay is more sensitive to CPU, frequency and transmission power. Decoupling does so by making the problem easier to solve through separation of devices, enabling multi-threaded parallel computation. The next communication active and energy allocation is decided according to the communication resource allocation. This repeats until the training time is at its appropriate bottom line which leads to the formation of certain energy harvesting strategies of efficient IoT devices.[8][9][11]

FUTURE ENHANCEMENTS

Such an opportunity for diversification of its spectrum by the model offers immense opportunities for provision of energy to ensure performance to be smooth and sustainable in applications that work on heterogeneous environments with different kinds of energy sources, like wind and bio-energy. Integration with machine learning further increases the scope by providing predictions related to energy availability to improve data management and power up applications. In addition, scalability has been addressed in the framing of the model as a solution instead of a growth limitation to be able to support the efficient transfer within increasingly complex and expansive IoT networks. Energy-efficient encryption has been considered to protect the IoT updates with no loss of performance for security purposes. All of these features improve adaptability, efficiency, and resilience in the model and can better respond to real-world IoT applications. [10]

CONCLUSION

This paper presents a new paradigm of the model for energy harvesting data management, focusing on power-constrained IoT systems all over the world. By combining renewable energy sources with intelligent data management strategies, it offers a sustainable concept that minimizes dependence on finite battery power, therefore extending the operational lifespan of IoT devices. The Cisco Packet Tracer simulation further demonstrates the feasibility and reliability of this model and also shows that it can perform stably under energy-variable scenarios. It, therefore, enables the continuous flow of data in energy-constrained worlds while addressing global sustainability concerns by minimizing electronic waste, thereby promoting a greener IoT development landscape.

Thus, the work hypothesizes greater breadth for the model in the various sectors like smart cities, environment monitoring, healthcare, and industrial automation. With an open-ended nature of growth in the IoT ecosystem, optimising factors around energy consumption and continuous operationalization will be key. In future work, therefore, steps will be taken to extrapolate the methodology to larger complex IoT networks and further consolidate the technology to newer set, such as 5G and AI-motivated data processing for improved performance and adaptability in IoT systems.

REFERENCES

1. Sanislav, T., Mois, G. D., Zeadally, S., & Folea, S. C. (2021). Energy Harvesting Techniques for Internet of Things (IoT). *IEEE Access*, *9*, 39530–39549. https://doi.org/10.1109/access.2021.3064066
2. Ejaz, W., Naeem, M., Shahid, A., Anpalagan, A., & Jo, M. (2017). Efficient Energy Management for the Internet of Things in Smart Cities. *IEEE Communications Magazine, 55*(1), 84–91. https://doi.org/10.1109/mcom.2017.1600218cm
3. Sadeeq, M. a. M., & Zeebaree, S. (2021). Energy Management for Internet of Things via Distributed Systems. *Journal of Applied Science and Technology Trends, 2*(02), 59–71. https://doi.org/10.38094/jastt20285
4. Saraereh, O. A., Alsaraira, A., Khan, I., & Choi, B. J. (2020). A Hybrid Energy Harvesting Design for On-Body Internet-of-Things (IoT) Networks. *Sensors*, *20*(2), 407. https://doi.org/10.3390/s20020407
5. DeFeo, C. (2015). Energy harvesting and the internet of things. In *Green Information Technology* (pp. 151-160). Morgan Kaufmann.
6. Shafique, K., Khawaja, B. A., Khurram, M. D., Sibtain, S. M., Siddiqui, Y., Mustaqim, M., & Yang, X. (2018). Energy harvesting using a low-cost rectenna for Internet of Things (IoT) applications. *IEEE Access*, *6*, 30932-30941.
7. Sun, H., Yin, M., Wei, W., Li, J., Wang, H., & Jin, X. (2018). MEMS based energy harvesting for the Internet of Things: a survey. *Microsystem Technologies, 24*, 2853-2869.
8. Wang, D., Liu, H., Ma, X., Wang, J., Peng, Y., & Wu, Y. (2017). Energy harvesting for internet of things with heterogeneous users. *Wireless Communications and Mobile Computing, 2017*(1), 1858532.
9. Yao, J., & Ansari, N. (2018). Caching in energy harvesting aided Internet of Things: A game-theoretic approach. *IEEE Internet of Things Journal*, *6*(2), 3194-3201.
10. Chang, H. C., Lin, H. T., & Wang, P. C. (2023). Wireless Energy Harvesting for Internet-of-Things Devices Using Directional Antennas. *Future Internet, 15*(9), 301.
11. Xing, P., Zhang, H., Derbali, M., Sefat, S. M., Alharbi, A. H., Khafaga, D. S., & Sani, N. S. (2023). An efficient algorithm for energy harvesting in IIoT based on machine learning and swarm intelligence. *Heliyon*, *9*(7).