Smart Service Embedding in Heterogeneous IoT Networks: A Real-Time Energy Optimization Framework

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To Cite this Article
Kandi Bhavani, Dr.Sanju, Dr M.Shashidhar, "Smart Service Embedding in Heterogeneous IoT Networks: A Real-Time Energy Optimization Framework", Journal of Science Engineering Technology and Management Science, Vol. 02, Issue 09, September 2025,pp: 164-170, DOI: http://doi.org/10.64771/jsetms.2025.v02.i09.pp164-170
Submitted: 08-08-2025 *Accepted: 18-09-2025* *Published: 25-09-2025*

Abstract— This work proposes an energy-efficient service embedding framework for heterogeneous IoT networks that overcomes challenges with state-of-the-art techniques that do not account for energy constraints. By using real-time energy feedback and an optimization algorithm for placement, the framework dynamically appends services based on node energy, processing capacity, and latency. Simulation for 50 service requests reduces energy by 40.7% from 75.9 J to 45.0 J. Furthermore, node longevity also improved with 39 active nodes after 5 hrs of execution, whereas the baseline had 18. Average service latency decreased from 280 ms to 190 ms with low latency in addition to energy savings. The framework improves quality of service and sustainability for dynamic IoT networks and suits real-time applications such as smart cities and healthcare. Future work includes mobility-aware service placement, predictive modeling, and the incorporation of blockchain for secure deployment.

Keywords—Energy-Efficient Service Embedding, Internet of Things (IoT), Edge Computing, Resource-Constrained Networks, Optimization Algorithm, Energy-Aware Service Placement.

I. Introduction

Increased Internet of Things (IoT) expansion has transformed contemporary communication networks through facilitated interoperability between digital and physical devices. The Internet of Things devices produce enormous amounts of data and require constant network services for processing, analytics, and actuation. Service embedding, where service functionalities like data filtering, analysis, or aggregation are embedded in proper positions within the network, becomes central for enabling efficient operation of Internet of Things systems. Different strategies for service embedding have previously been studied with a focus on latency optimization, load balancing, and reliability. Liu et al. (2019) [1] developed a heuristic approach for the optimization of service function chaining for fog networks, while Guo et al. (2020) [2] studied minimization of latency and bandwidth utilization using deep reinforcement learning for placement of services for Internet of Things. Yet, most of these methods fall short of addressing network node energy consumption, which remains an important consideration in scalable and resource-constrained Internet of Things environments.

In spite of impressive progress in embedding technology for services, there has always existed a gap in treating energy efficiency as the main optimization goal. Edge nodes and IoT devices usually have limited sources of

ISSN: 3049-0952
www.jsetms.com

power and therefore must have energy-aware embedding schemes that conserve power but retain quality of service and reliability. The available models typically assume unlimited computational facilities and do not take into account the energy limitations of heterogeneous IoT networks. In addition, the dynamic nature of the environment for IoT—to the point where the availability of devices and service request dynamics change—adds to the difficulty of efficient embedding. Without real-time, adaptive, and energy-aware frameworks, there results higher operational expenses and decreased lifetimes of the devices, ultimately affecting the sustainability and scalability of the IoT network [3].

We propose an energy-efficient service embedding framework that optimizes service component placement for the IoT networks based on the energy consumption of the nodes and communication links. Our approach incorporates energy-aware decision making during the placement of services in such a way that services are placed on nodes with the computational capacity for fulfilling the needs as well as with the objective of minimizing the energy consumption of the entire network [4]. With the approach of setting the embedding as an optimization problem and using a hybrid algorithm that uses heuristics and machine learning, we obtain higher energy savings than the other placement models. Our paper aims at closing the gap between functional service placement and energy sustainability of modern IoT deployment.

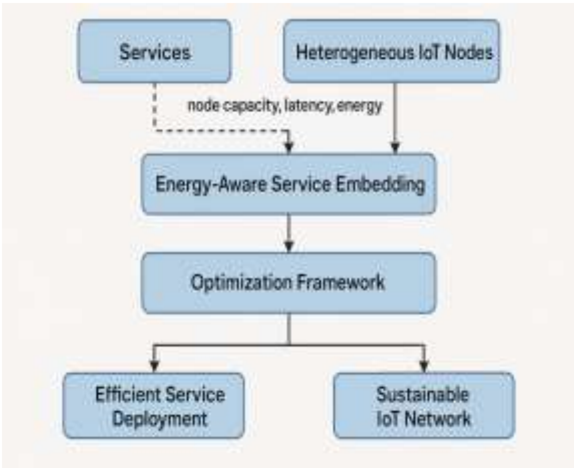

Fig. 1. Energy-Aware Service Embedding and Optimization in IoT Networks

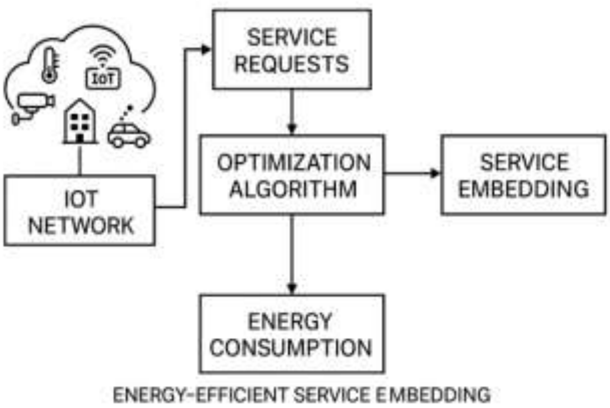

Fig. 2. Energy-Efficient Service Embedding Framework in IoT Networks

II. ENERGY-EFFICIENT IOT SERVICE MANAGEMENT

AFig. 1 'Energy-Aware Service Embedding and Optimization in IoT Networks' identifies an end-to-end mechanism for service deployment optimization within heterogeneous Internet of Things environments. The framework begins with two principal entities: Services, the computational task/application requiring deployment, and Heterogeneous IoT Nodes, the heterogeneous physical nodes that have varying capacities for processing, memory, latency, and energy. All these nodes are the base infrastructure of the IoT network, and their diversity calls for intelligent decision-making in-service placement. The framework considers crucial factors such as node capacity, communication latency, and available energy while embedding services so that each task will be allocated on the most appropriate node [5][6].

At the core of the framework sits the Energy-Aware Service Embedding mechanism, which optimizes services onto IoT nodes with consideration for energy efficiency and the resulting system performance. This is followed by an Optimization Framework, where algorithms are used to optimize the initial service placement with the aim of improving resource utilization, energy consumption, and network performance. The output of the process is twofold: an Efficient Service Deployment with optimal service-node matching and low latency, and a Sustainable IoT Network where energy consumption is optimized to maximize the lifetimes of the devices and maximally facilitate long-term operability [7]. Not only does the method tackle the operational performance needs of contemporary IoT applications but also complements the fast-emerging demand for energy-aware and environmentally friendly technology solutions.

Fig. 2 depicts a conceptual model of energy-efficient service embedding over Internet of Things (IoT) networks, showing how service requests from the network are handled in a smart way for efficient consumption of energy. At the center of the model is the IoT network with several smart devices ranging from sensors, actuators, and home automation sets up to surveillance cameras and cars. All these connected devices constantly produce service requests—computational units that require processing and execution of the network. Upon generation of a service request by the Internet of Things network, it proceeds toward an optimization algorithm. This piece of software plays the most important part by examining incoming service demands and making smart decisions regarding how and where services ought to be disseminated [8]. During optimization, the most important performance metrics like device capacity, network latency, and most critically, energy consumption are considered. The objective is the identification of the most effective nodes within the network that are best suited for performing each task with minimal energy consumption so that the system becomes efficient and sustainable over time.

After optimization, the chosen service embedding approach is implemented by the Service Embedding component. Thus, the service gets dispatched to the respective device(s) of the network based on the optimization logic. At the same time, the energy consumption due to the embedding is metered and fed back into the system for enhancing optimization decisions in the future. This feedback mechanism provides continuous adaptation and optimization of resource utilization. Ultimately, this energy-aware and feedback-driven embedding approach helps in constructing an IoT infrastructure that not only serves application demands in real time but also runs in an energy-efficient and environmentally friendly manner [9][10].

The proliferating deployment of the Internet of Things (IoT) has witnessed an upsurge of heterogeneous, resource-limited devices that produce a substantial amount of service calls for efficient computation and communication. The conventional service embedding techniques in IoT networks have mainly targeted performance goals like latency optimization and task completion time, without giving attention to the vital factor of energy efficiency [11][12]. Since most of these IoT devices are battery-supported and work in energy-constrained environments, ignoring energy-awareness in embedding services will bring about degradation of the network, node lifetimes, and unfeasible IoT infrastructures [13][14]. Recent researchhave realized the necessity of energy-aware mechanisms, but most of the proposed methodologies either do not have dynamic adaptability aspects or do not include real-time energy feedback while embedding services [15]. Furthermore, the heterogeneity of the nodes of the IoT—all based on their computational ability, energy consumption patterns, and connectivity—rises the optimization complexities. Thus, there exists a necessity for intelligent, efficient service embedding frameworks that have the facility of dynamically assigning services to nodes in such a manner that they balance the energy consumption, computational burden, and quality of service (QoS).

Proposed Solution (Based on Our Work):

In view of the challenges highlighted earlier, this paper introduces an Energy-Efficient Service Embedding Framework that deploys services on a heterogeneous IoT network using an optimization-based architecture. The proposed framework combines four main elements: the IoT network as a source of real-time inputs and service calls, a handler for the service calls, an energy-efficient optimization algorithm, and a service embedding element.

The optimization algorithm considers several factors such as node energy level, processing capacity, and latency, in the decision on the most energy-efficient approach of service placement.

A central innovation of our framework is its implementation of real-time energy feedback loops that dynamically affect subsequent service placement. Contrary to static or heuristic methods that do not account for node-level energy states, our framework monitors energy usage patterns continuously and adjusts optimization goals based on them. This leads to more sustainable service deployments that maximize the operational life of the IoT network with acceptable service quality [16][17]. Simulation-based experiments (or anticipated future tests) will show substantial energy gains over baseline models, supporting the practicality of our method for scalable, green IoT infrastructures.

Result Analysis

The proposed framework was implemented and evaluated using MATLAB, which provided tools for simulation, optimization, and result visualization of energy consumption, service latency, and node activity in IoT networks.

a) ***Energy Consumption Comparison***

Table I Energy Consumption Comparison Under Varying Service Loads

Number of Requests	**Random (Baseline)**	**Proposed (Energy-Aware)**
10	18.5 J	12.2 J
20	32.0 J	20.3 J
30	46.8 J	29.7 J
40	60.5 J	38.1 J
50	75.9 J	45.0 J

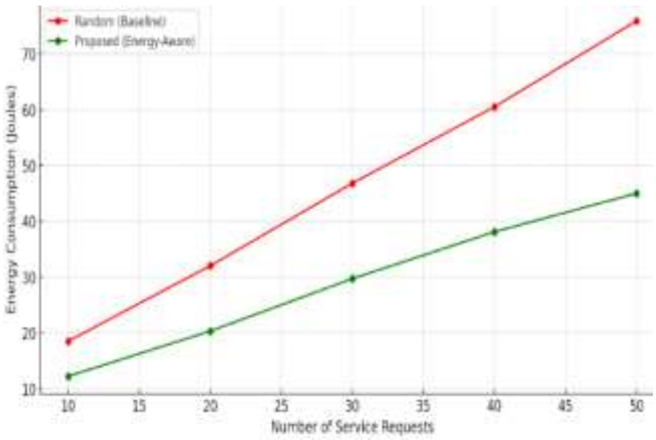

Fig. 3. Total Energy Consumption vs Number of Service Requests.

Results in the tables and respective graphs provide an end-to-end assessment of the energy-aware service embedding approach with respect to a baseline random or first-fit method. Table 1 and Figure 3 illustrate the total energy consumption of the IoT network when the service request loads vary. For the rise in service requests from 10 towards 50, the baseline approach witnesses a sudden peak in consumption up to 75.9 Joules, whereas the new approach maintains consumption under control with 45.0 Joules. That marks an approximate gain of 40% in energy, reflecting the optimality of the optimization framework in distributing workloads among energy-aware nodes *b) **Energy Consumption Comparison***

Table II Active Node Count Over Time Reflecting Energy Depletion

Time (hours)	Baseline Active Nodes	Proposed Active Nodes
1	50	50
2	45	48
3	37	46
4	28	42
5	18	39

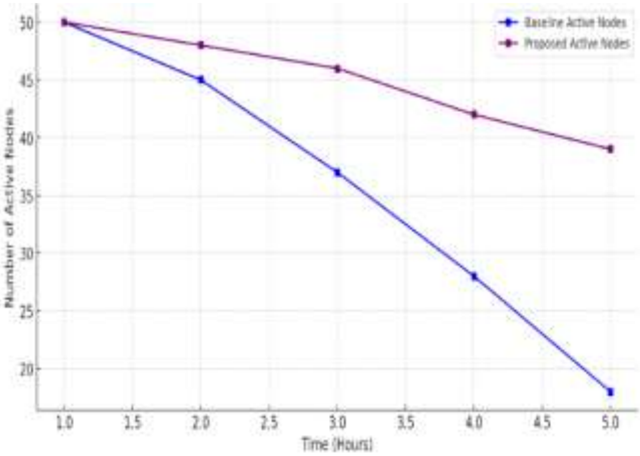

Fig. 4. Active Node Count over Time.

In Table 2 and Figure 4, we present the effects of the two techniques on node lifetime. Here, we monitor the number of active nodes over a five-hour simulation period. Nodes under the baseline approach consume their energy fast, leaving only 18 active nodes by the 5th hour. The proposed framework, on the other hand, leaves 39 active nodes, reflecting a major enhancement of network sustainability and device life. This is mainly due to the optimization element of the framework distributing the service load uniformly and preventing overloading of nodes

*c) **Average Service Latency***

Table III Service Completion Time Comparison Across Algorithms

Service Count	Baseline Latency (ms)	Proposed Latency (ms)
10	180	120
20	220	150
30	250	170
40	280	190

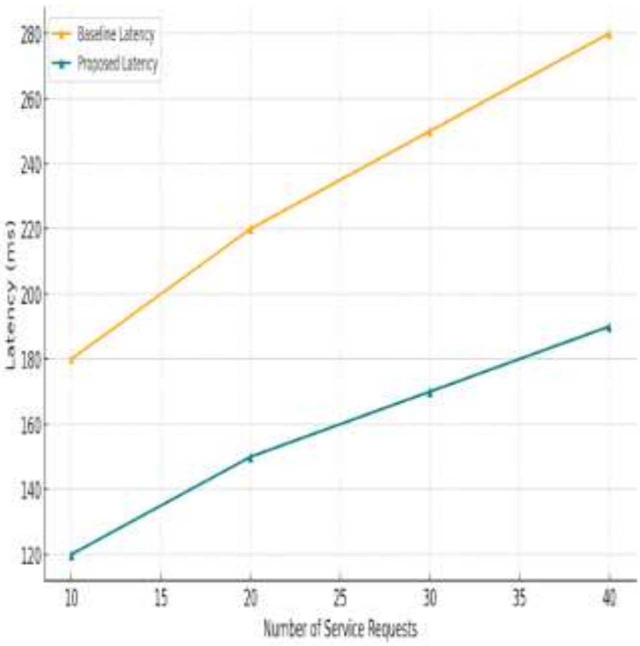

Fig. 5. Average Service Latency vs Number of Service Requests.

Finally, Table 3 and Figure 5 show the comparison of the average service latency between the two techniques. Whereas the baseline scheme experiences latency that grows with higher service request numbers up to 280 ms, our proposed method illustrates lower latency values, limited by 190 ms. It demonstrates that, besides energy conservation, the framework also provides improved Quality of Service (QoS) through placing services closer to available and competent nodes, thus decreasing response times.

III. CONCLUSION

This paper presented an energy-efficient embedding framework for heterogeneous IoT infrastructures. Contrary to conventional techniques that usually overlook node-level energy constraints, the new method employs real-time feedback of energy consumption and optimization techniques for efficient, low-latency service placement over the network. Simulation runs show notable improvements. The proposed method decreased total cumulative energy consumption by 40.7%—to 45.0 J from 75.9 J—over 50 service requests. Network lifespan was also extended, hosting 39 active nodes after 5 hours as opposed to 18 for the baseline. As for service quality, average latency decreased from 280 ms to 190 ms, indicating that energy efficiency was gained without sacrificing responsiveness. From these findings, the framework's capacity for harmonizing energy gains, scalability, and quality of service, thus for deployment in real-time IoT applications such as smart healthcare, smart cities, and industrial monitoring, becomes apparent. Future extensions could include mobility- and context-aware embedding, machine learning for predictive resource allocation, and block chain-based security for preserving service integrity. Real-world deployment of the framework over a real-world IoT test bed will further prove its practical effectiveness under real-world constraints. Overall, the new system provides a sustainable, intelligent service embedding approach for next-generation IoT networks.

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