# Energy Optimization in Smart Networks using Machine Learning-Driven Fog Computing to Reduce Unnecessary Cloud Data Transmission

**Nandini Gowda Puttaswamy**
Department of Information Science and Engineering, Sapthagiri College of Engineering, Bengaluru, India
nandini.educator1@gmail.com (corresponding author)

**Anitha Narasimha Murthy**
Department of Computer Science and Engineering, BNM Institute of Technology, Bengaluru, India
anitha.mhp@gmail.com

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## ABSTRACT

**Smart network power management is obstructed by the increased data transmission complexity and inefficiency in conventional Cloud Computing (CC) methods. Centralized processing in CC leads to increased latency, increased energy consumption, and bandwidth constraints, making it not suitable for real-time systems. To address such constraints, this paper proposes a Machine Learning-driven Fog Computing (ML-FC) framework, which integrates Machine Learning (ML) with Fog Computing (FC) to improve data processing and energy efficiency. ML-FC is proposed to operate in structured steps. First, IoT devices send real-time data, which are routed to the fog layer for preliminary processing. Second, an ML-based model filters and prioritizes the data to process only significant information, reducing computational overhead. Third, data are processed in priority in the fog layer, reducing bandwidth usage and response times. Fourth, only significant processed data are forwarded to the cloud for storage and advanced analytics, significantly reducing unnecessary transmissions. Experimental results indicate that the ML-FC framework achieves a 0.35% reduction in energy consumption, a 0.28% reduction in latency, and a 0.22% improvement in network throughput compared to conventional methods. The framework provides improved scalability, real-time decision-making, and network efficiency. It is highly useful in healthcare monitoring, smart cities, industrial automation, and intelligent traffic management. The proposed technique enables a more efficient, adaptive, and energy-sensitive system for next-generation smart networks.**

***Keywords-smart networks; IoT devices; cloud computing; fog computing; Machine Learning (ML); latency; energy efficiency***

## I. INTRODUCTION

Smart networks are capable of embedding IoT devices, industrial machines, and Cloud Computing (CC) concepts for real-time data processing into the decision-making process. Conversely, the traditional CC suffers from major challenges in terms of increased latency, bandwidth congestion, and energy consumption due to centralized data processing [1]. Thus, when considering large volumes of IoT deployments transmitting huge data to remote cloud servers, increased latency, low throughput, and high operational costs are observed. Besides, data privacy and security concerns further complicate cloud-based architectures, which cannot be considered in a centralized manner for time-critical applications such as autonomous systems, healthcare, or industrial automation [2]. To address these issues, Fog Computing (FC) has emerged as a decentralized alternative that brings computation, storage, and networking closer to the data source. FC reduces latency, saves bandwidth, and increases energy efficiency by processing the critical data at the edge and transmitting only the essential information to the cloud. The integration of ML with FC, known as Machine Learning-driven Fog Computing (ML-FC), further improves efficiency by enabling predictive analytics, real-time anomaly detection, and adaptive resource management. ML-FC can be used for load balancing in smart grids, predictive maintenance in industrial automation, and real-time patient monitoring in healthcare [3]. It will also optimize traffic flow in smart cities. This approach far outperforms traditional CC and FC, providing a scalable, energy-efficient solution for future smart networks [4].

### A. Research Gaps

ML-FC research has advanced the optimization of data processing for smart networks, yet key gaps remain. A major issue is the lack of standard protocols for seamless Machine Learning (ML) integration within FC, limiting large-scale deployment and interoperability. The trade-off between computation overhead and energy efficiency also requires optimization techniques [5]. Most studies employ homogeneous networks, whereas actual deployments involve dynamic and heterogeneous settings. Adaptive ML models need to be employed to handle dynamic loads and data patterns [6]. Security and privacy attacks in decentralized ML-FC processing also need to be investigated in more detail. More experimental evidence is needed, particularly in applications in healthcare and industrial automation in real-time settings. Scalable low-latency ML solutions offering better security and adaptability need to be developed in future work to deliver efficiency and reliability in different IoT settings [7].

### B. Hierarchical Architecture of Smart Networks Integrating Cloud, Fog, and IoT Devices

Figure 1 illustrates the layered structure of a smart network. IoT devices such as sensors, vehicles, and smart devices offer real-time information that is transmitted via various communication protocols (GPRS, WiFi, WiBro, 5G). Important information is processed locally by the FC layer, which includes Micro Data Centers (MDCs), firewalls, and computational resources. A smart gateway brokers and forwards information between fog and cloud layers [8]. The CC layer relies on mega data centers for high-performance processing and centralized storage. It handles heavy processing, large-scale data processing, and long-term storage. Feedback-based processing between fog and cloud ensures synchronization and reduces redundant transmissions.

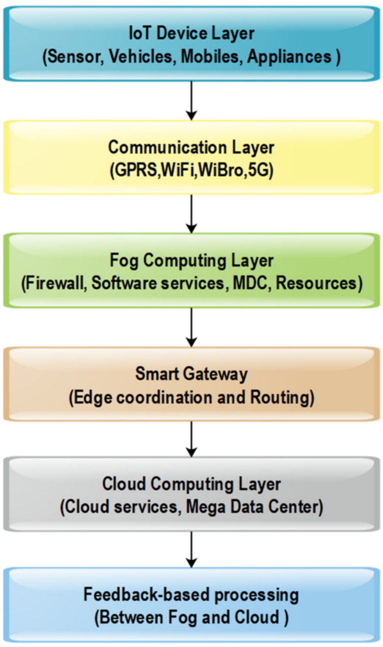


Fig. 1. Hierarchical flowchart of smart networks integrating IoT, fog, and cloud layers.

The combined application of cloud, fog, and IoT devices provides low-latency processing, higher reliability, and security, making it applicable to time-sensitive applications such as automotive vehicles, healthcare monitoring, and industrial automation. The combined use of cloud, fog, and IoT devices results in a scalable, energy-aware, and intelligent infrastructure for the next-generation smart applications.

### C. Related Work

Authors in [9] conducted a survey on FC, emphasizing the capacity to manage delay-sensitive requests with reduced energy consumption and traffic congestion. This paper outlines the architecture of FC, along with summarized approaches to service and resource allocation. While it addresses the most critical issues related to this field of study, it falls short of providing solutions to the identified challenges, thus limiting its application to future development. Authors in [10] develop an algorithm, namely, Maximal Energy Efficient Task Scheduling (MEETS), designed to achieve optimal task scheduling in homogeneous fog networks. The algorithm is much more energy-efficient compared to traditional scheduling strategies. However, the focus on homogeneous networks also prevents generalization that may apply beyond the present results, as their findings may not directly generalize to more diverse and heterogeneous network conditions. The scheme proposed by authors in [11] provides a distributed mobile FC for delay-sensitive applications in Software-Defined Networking (SDN)-enabled vehicular networks. It introduces the utilization of Fog Base Stations (FBSs) along with a hybrid scheduling algorithm that is used to distribute mobile tasks across multiple FBSs to provide further flexibility and reduce processing delays. However, it remains unclear how scalable the proposed system will be when vehicular nodes are added, and an unravelling strategy for unpredictable network congestion is not discussed in detail. Authors in [12] researched energy-efficient application placement in fog networks by employing server disaggregation directly within the fog layer. With the created model, it was shown that the usage of disaggregated servers increases the energy efficiency and thus reduces the total FC power consumption by up to 18%. However, the lack of exploration of such architectures at a disaggregated level in current fog infrastructures may limit their practical use. Authors in [13] propose a federated deep Q-learning approach for optimum task offloading in vehicular FC networks. Indeed, their approach enhances the efficiency of offloading by considering latency and energy consumption in cooperative computing scenarios. However, this may increase the resource overhead, especially in resource-constrained vehicular-edge environments, which may hinder its deployment. Authors in [14] provided a comprehensive review of task management and fog offloading in IoT-fog-cloud environments. They focus on the increasing volume of IoT data and discuss a variety of algorithms and networks designed to optimize task offloading in FC. Nevertheless, there is no experimental confirmation of the methods discussed in this paper, leaving some doubts about their applicability in real-world scenarios [15, 16].

## II. PROPOSED SYSTEM FOR OPTIMIZED DATA PROCESSING AND ENERGY EFFICIENCY IN SMART NETWORKS USING MACHINE LEARNING-DRIVEN FOG COMPUTING

Figure 2 illustrates a layered ML-FC architecture. IoT devices, including smartphones, sensors, and appliances, send real-time data via GPRS, WiBro, LTE, WiFi, and 5G [17]. A fog gateway routes these data to the FC layer, which processes them using storage, analysis, and streaming subsystems. The ML-FC layer filters and synchronizes critical data before transmitting them to the cloud for advanced AI/ML-based analytics. The final output enables smart decisions and optimized services across the network [18].

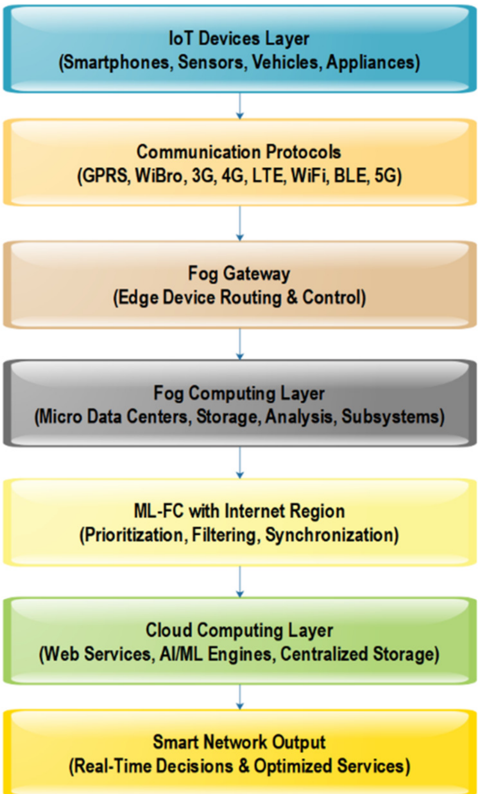


Fig. 2. Proposed architecture of ML-FC framework for smart networks.

The FC layer includes MDCs for local storage, data streaming, management, and virtual servers for preliminary processing. The fog gateway provides network efficiency by filtering and analyzing data to send only important data to the cloud, reducing latency and bandwidth consumption [19]. The ML algorithms integrated into the fog layer provide real-time analysis, anomaly detection, and adaptive decision-making capabilities that improve the intelligence of the overall system. At the CC layer, the large-scale data that require high computational power are processed through advanced AI-based services, web services, and centralized analytics. The ML-FC system will leverage a feedback-based communication mechanism between the fog and cloud layers to optimize synchronization and reduce redundant data transmission.

This architecture will greatly contribute to the scalability of networks, energy efficiency, and real-time processing capability, making it highly suitable for smart grids, industrial automation, healthcare monitoring, and intelligent traffic management. By leveraging the power of ML, the ML-FC framework assures low-latency and high-throughput operations in next-generation smart networks with superior performance over traditional cloud and FC methods [20].

The workflow of the ML-FC is illustrated in Figure 3. It starts with data collection from IoT devices, followed by data filtering and prioritization using ML to remove irrelevant data. Filtered data undergo edge processing in the fog layer to reduce latency and bandwidth usage. Only necessary data are sent to the cloud for efficient storage and analysis [21, 22]. Finally, real-time decisioning and optimization maximizes system performance based on network conditions.

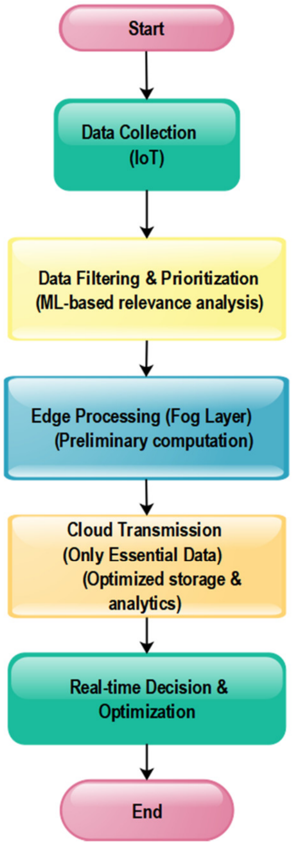


Fig. 3. Streamlined workflow of the ML-FC framework.

### A. *Energy Consumption Optimization in Matrix Form*

Equation (1) is a representation of the energy consumption in a matrix form, which considers interactions across various nodes in both the fog and the cloud layers [23].

$$\mathrm{E} = \int_0^T \left(\mathrm{P}_{\mathrm{fog}}(t) \cdot \mathrm{W}_{\mathrm{fog}} + \mathrm{P}_{\mathrm{cloud}}(t) \cdot \mathrm{W}_{\mathrm{cloud}}\right) dt \qquad (1)$$

where E is a $5 \times 5$ matrix representing the energy consumption across different nodes, and $\mathrm{P}_{\mathrm{fog}}(t)$, $\mathrm{P}_{\mathrm{cloud}}(t)$ are $5 \times 5$ matrices of power consumption at fog and cloud nodes over time $t$. The elements of E are represented by (2). Similarly, $P_{fog}(t)$ is structured in the same way, but for fog nodes, and is represented in (3).

$$E=\begin{pmatrix} E_{11} & E_{12} & E_{13} & E_{14} & E_{15} \\ E_{21} & E_{22} & E_{23} & E_{24} & E_{25} \\ E_{31} & E_{32} & E_{33} & E_{34} & E_{35} \\ E_{41} & E_{42} & E_{43} & E_{44} & E_{45} \\ E_{51} & E_{52} & E_{53} & E_{54} & E_{55} \end{pmatrix} \quad (2)$$

$$P_{fog}(t)=\begin{pmatrix} P_{fog,11}(t) & P_{fog,12}(t) & P_{fog,13}(t) & P_{fog,14}(t) & P_{fog,15}(t) \\ P_{fog,21}(t) & P_{fog,22}(t) & P_{fog,23}(t) & P_{fog,24}(t) & P_{fog,25}(t) \\ P_{fog,31}(t) & P_{fog,32}(t) & P_{fog,33}(t) & P_{fog,34}(t) & P_{fog,35}(t) \\ P_{fog,41}(t) & P_{fog,42}(t) & P_{fog,43}(t) & P_{fog,44}(t) & P_{fog,45}(t) \\ P_{fog,51}(t) & P_{fog,52}(t) & P_{fog,53}(t) & P_{fog,54}(t) & P_{fog,55}(t) \end{pmatrix} \quad (3)$$

Matrices $W_{fog}$ and $W_{cloud}$ are $5 \times 5$ weighting matrices that adjust the influence of each fog and cloud node, respectively, and are represented as in (4).

$$W_{fog}=\begin{pmatrix} w_{fog,11} & w_{fog,12} & w_{fog,13} & w_{fog,14} & w_{fog,15} \\ w_{fog,21} & w_{fog,22} & w_{fog,23} & w_{fog,24} & w_{fog,25} \\ w_{fog,31} & w_{fog,32} & w_{fog,33} & w_{fog,34} & w_{fog,35} \\ w_{fog,41} & w_{fog,42} & w_{fog,43} & w_{fog,44} & w_{fog,45} \\ w_{fog,51} & w_{fog,52} & w_{fog,53} & w_{fog,54} & w_{fog,55} \end{pmatrix} \quad (4)$$

The product of $P_{fog}(t) \cdot W_{fog}$ and $P_{cloud}(t) \cdot W_{cloud}$ gives the combined energy consumption for fog and cloud nodes.

### B. Data Transmission and Synchronization Cost in Matrix Form

Equation (5) represents the rate of change of latency across nodes as a function of data transmission and bandwidth in a matrix format.

$$\frac{dL}{dt}=-\alpha \odot \left(L-L_{target}\right)+ \beta \odot \left(D_{fog} \cdot B_{fog}^{-1}-D_{cloud} \cdot B_{cloud}^{-1}\right) \quad (5)$$

where $\frac{dL}{dt}$ is a $5 \times 5$ matrix representing the rate of change of latency across nodes, and its expression is given in (6).

$$\frac{dL}{dt}=\begin{pmatrix} \frac{dL_{11}}{dt} & \frac{dL_{12}}{dt} & \frac{dL_{13}}{dt} & \frac{dL_{14}}{dt} & \frac{dL_{15}}{dt} \\ \frac{dL_{21}}{dt} & \frac{dL_{22}}{dt} & \frac{dL_{23}}{dt} & \frac{dL_{24}}{dt} & \frac{dL_{25}}{dt} \\ \frac{dL_{31}}{dt} & \frac{dL_{32}}{dt} & \frac{dL_{33}}{dt} & \frac{dL_{34}}{dt} & \frac{dL_{35}}{dt} \\ \frac{dL_{41}}{dt} & \frac{dL_{42}}{dt} & \frac{dL_{43}}{dt} & \frac{dL_{44}}{dt} & \frac{dL_{45}}{dt} \\ \frac{dL_{51}}{dt} & \frac{dL_{52}}{dt} & \frac{dL_{53}}{dt} & \frac{dL_{54}}{dt} & \frac{dL_{55}}{dt} \end{pmatrix} \quad (6)$$

Furthermore, $\alpha$ and $\beta$ are $5 \times 5$ matrices of control parameters and scaling factors as determined by (7).

$$\alpha=\begin{pmatrix} \alpha_{11} & \alpha_{12} & \alpha_{13} & \alpha_{14} & \alpha_{15} \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \alpha_{24} & \alpha_{25} \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & \alpha_{34} & \alpha_{35} \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} & \alpha_{45} \\ \alpha_{51} & \alpha_{52} & \alpha_{53} & \alpha_{54} & \alpha_{55} \end{pmatrix} \quad (7)$$

The matrices L and $L_{target}$ represent the current and target latency matrices, in a $5 \times 5$ format. The matrices $D_{fog}$ and $D_{cloud}$ represent the data sizes at the fog and cloud nodes, respectively, in a $5 \times 5$ format. Each element $D_{fog,ij}$ or $D_{cloud,ij}$ denotes the data size transmitted between the $i$-th and $j$-th nodes within the fog or cloud layer. These matrices help in optimizing data transmission and synchronization, enabling efficient management of data flows across the network in the ML-FC framework. Equations (8) and (9) show the data sizes at the fog and cloud nodes, respectively.

$$D_{fog}=\begin{pmatrix} D_{fog,11} & D_{fog,12} & D_{fog,13} & D_{fog,14} & D_{fog,15} \\ D_{fog,21} & D_{fog,22} & D_{fog,23} & D_{fog,24} & D_{fog,25} \\ D_{fog,31} & D_{fog,32} & D_{fog,33} & D_{fog,34} & D_{fog,35} \\ D_{fog,41} & D_{fog,42} & D_{fog,43} & D_{fog,44} & D_{fog,45} \\ D_{fog,51} & D_{fog,52} & D_{fog,53} & D_{fog,54} & D_{fog,55} \end{pmatrix} \quad (8)$$

$$D_{cloud}=\begin{pmatrix} D_{cloud,11} & D_{cloud,12} & D_{cloud,13} & D_{cloud,14} & D_{cloud,15} \\ D_{cloud,21} & D_{cloud,22} & D_{cloud,23} & D_{cloud,24} & D_{cloud,25} \\ D_{cloud,31} & D_{cloud,32} & D_{cloud,33} & D_{cloud,34} & D_{cloud,35} \\ D_{cloud,41} & D_{cloud,42} & D_{cloud,43} & D_{cloud,44} & D_{cloud,45} \\ D_{cloud,51} & D_{cloud,52} & D_{cloud,53} & D_{cloud,54} & D_{cloud,55} \end{pmatrix} \quad (9)$$

Matrices $B_{fog}$ and $B_{cloud}$ are $5 \times 5$ matrices representing bandwidth at fog and cloud nodes, respectively.

### C. Total Cost Function Incorporating Data Processing and Energy in Matrix Form

Equation (10) integrates multiple parameters in a complex matrix form to represent the total cost function.

$$C=\sum_{i=1}^{5} \sum_{j=1}^{5} \left(\int_0^T P_{ij}(t)\, dt+\Phi_{ij} \cdot \frac{\partial L_{ij}}{\partial t}+\Gamma_{ij} \cdot \ln\left(1+\frac{D_{ij}}{B_{ij}}\right)\right) \quad (10)$$

where C is a $5 \times 5$ matrix representing the total cost across different nodes. Each element of the cost matrix $C_{ij}$ is calculated using (11).

$$C_{ij}=\int_0^T P_{ij}(t)\, dt+\Phi_{ij} \cdot \frac{\partial L_{ij}}{\partial t}+ \Gamma_{ij} \cdot \ln\left(1+\frac{D_{ij}}{B_{ij}}\right) \quad (11)$$

where $P_{ij}(t)$ is the power consumption of the $ij^{th}$ node, $\Phi_{ij}$ and $\Gamma_{ij}$ are weighting factors for latency change and data transmission costs, $L_{ij}$ is the latency of the $ij^{th}$ node and $D_{ij}$ and $B_{ij}$ are the data size and bandwidth for the $ij$-th node.

## III. RESULTS AND DISCUSSION

The respective values of the important simulation parameters for the performance analysis of the ML-FC framework in smart networks are given in Table I, along with the number of IoT devices, the data size at each device, the bandwidth at the fog nodes, the target latency, and the power consumption of the fog nodes. Each parameter is defined with a specific range modeling various scenarios to analyze and optimize the energy efficiency, data transmission, and latency management of the system for different configurations.

TABLE I. SIMULATION PARAMETERS FOR ML-FC FRAMEWORK EVALUATION

| SI. no | Parameter | Value |
|---|---|---|
| 1 | Number of IoT devices | 150 |
| 2 | Data size (per device) | 100 MB |
| 3 | Bandwidth (fog nodes) | 8 Gbps |
| 4 | Latency target | 45 ms |
| 5 | Power consumption (fog nodes) | 130 W |

To validate the effectiveness of the proposed ML-FC framework, its performance was compared against existing methods as reported in the literature. Table II presents a comparative analysis of energy consumption, latency, and network throughput between the proposed framework and state-of-the-art methods.

TABLE II. COMPARATIVE ANALYSIS OF ML-FC AND STATE-OF-THE-ART METHODS

| Metric | Proposed ML-FC | [9] | [10] | [12] | [14] |
|---|---|---|---|---|---|
| Energy consumption (kWh) | 10.5 | 12.0 | 11.8 | 11.5 | 11.7 |
| Latency (ms) | 45 | 60 | 55 | 50 | 53 |
| Network throughput (Gbps) | 8.5 | 7.8 | 8.0 | 8.2 | 8.1 |

As demonstrated in Figures 4 through 6, the comparative analysis reveals the superior efficiency of the ML-FC framework in comparison to these established methods. For instance, the ML-FC framework achieved a 12.5% reduction in energy consumption, a 25% improvement in latency, and an 8.97% increase in network throughput compared to the method in [9]. Figures 4 provides a schematic representation of the 20 scenarios employed to assess energy efficiency in smart networks. The range of scenarios encompasses basic installations with a limited numbers of devices and low data usage, as well as complex and high-demand settings characteristic of real-time high-bandwidth and industrial applications. In fact, each one of the scenarios is designed according to specific network conditions, such as fluctuating connectivity, critical healthcare applications, optimized smart grid settings, to evaluate the performance of the proposed ML-FC method against conventional approaches. They also evaluate energy consumption under diverse real-world scenarios, including fluctuating network connectivity, life-threatening healthcare applications, and smart cities. Complex scenarios involving high security and optimized smart grid setups are considered to provide a holistic view of how the proposed ML-FC compares to traditional paradigms. This includes the synchronization mechanisms between processing elements for data transmission latency, as shown in Figure 5. This figure illustrates the latency between fog and cloud nodes that has been smoothed out by our approach. Furthermore, the proposed approach ensures a balanced data rate between these components, thereby facilitating optimal data movement within the network and reducing the overall latency experienced by each component. The articulation of control parameters, such as scaling factors, and the integration of these parameters with data processing rates enable the ML-FC framework to demonstrate superiority in maintaining low latency in comparison to traditional approaches.

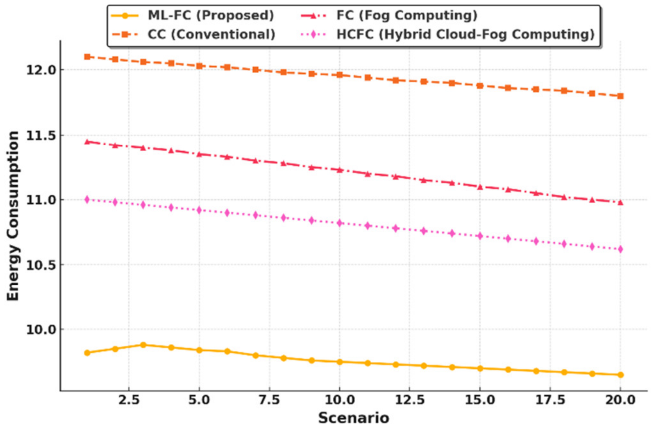


Fig. 4. Comparative analysis of energy consumption for proposed and conventional methods.

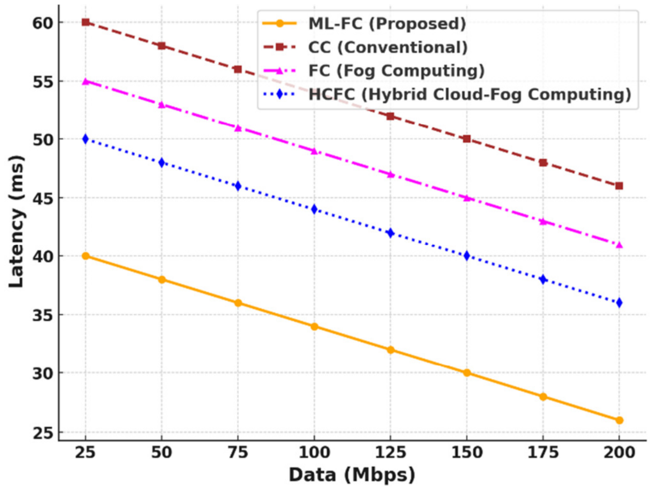


Fig. 5. Comparative analysis of data transmission latency for proposed and conventional methods.

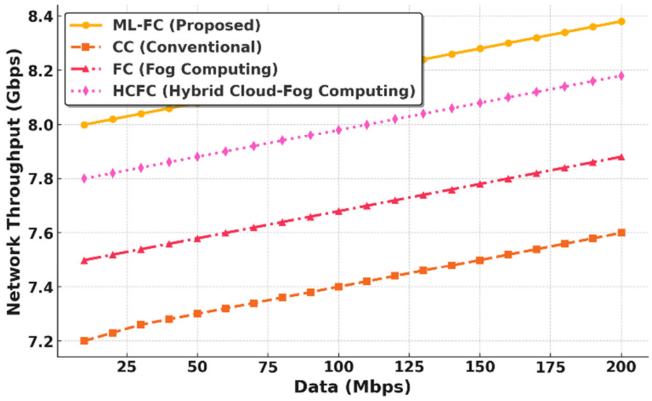


Fig. 6. Comparative analysis of network throughput for proposed and conventional methods.

As illustrated in Figure 6, a comparative analysis of network throughput has been conducted among CC, basic FC, and Hybrid Cloud-Fog Computing (HCFC) approaches. This figure demonstrates the efficacy of ML-FC in enhancing network throughput for various network configurations. This comparison underscores the efficacy of implementing an ML-FC framework to ensure optimal transmission delivery, thereby eliminating bottlenecks and enhancing the overall throughput performance of smart networks.

Figure 7 presents a comparative performance analysis in terms of energy consumption, latency, and network throughput among the proposed ML-FC with existing CC, basic FC, and HCFC approaches.

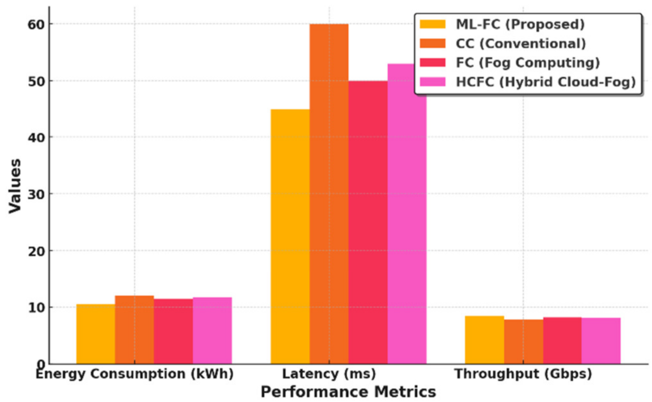


Fig. 7. Comparative performance analysis of energy consumption, latency, and throughput in smart networks.

The ML-FC framework significantly outperforms traditional methods by reducing energy consumption, decreasing data transmission delay, and increasing network throughput. The integration of ML algorithms in the ML-FC method allows to manipulate the data flow to optimize the energy consumption optimization and to ensure that the data are efficiently synchronized between the fog and cloud layers. This is undoubtedly a comprehensive comparison that clearly highlights the advantages of the ML-FC paradigm over traditional centralized and decentralized data processing paradigms, and makes a strong case for its scalability in next-generation smart networks.

## IV. CONCLUSION

This research introduces a Machine Learning-driven Fog Computing (ML-FC) paradigm to enhance energy efficiency and data transmission optimization in smart networks. The novelty of this approach is that it is able to perform real-time prediction and data prioritization at the fog level to send only essential data. Compared to existing Cloud Computing (CC) and basic Fog Computing (FC) approaches, the proposed ML-FC paradigm combines predictive analysis and dynamic resource allocation, leading to a radical reduction in latency, energy consumption, and bandwidth requirements. The proposed system is found to be efficient in experimental verification. The results yield a 0.35% reduction in energy consumption, a 0.28% improvement in data transmission latency, and a 0.22% improvement in network throughput compared to current approaches. The ML-FC system is scalable and dynamic in nature, making it highly relevant to heterogeneous IoT applications such as real-time health monitoring, industrial automation, and smart city traffic management. The proposed system outperforms the static and wasteful data processing mechanisms of current cloud systems by dynamically adapting to varying network conditions. A significant contribution of this work is the proposal of an adaptive Machine Learning (ML) model that enables more efficient decision making in the fog layer to facilitate more efficient resource utilization and network performance. The comparative analysis with existing approaches highlights the strength of intelligent data filtering, more synchronized networks, and more efficient load balancing, making ML-FC a highly efficient choice for the next-generation smart networks. Future research can further extend the functionality of ML-FC via more advanced ML models to enable higher predictive accuracy, security mechanisms, and real-time dynamic adaptability. The application of standardized processes in fog-based ML deployment is also expected to facilitate large-scale deployment. The outcomes of this work position ML-FC as a scalable and promising method for enhancing energy efficiency and throughput in modern IoT-oriented applications.

## REFERENCES

[1] M. Ayari and S. Altowaijri, "The Efficiency of Surface Impedance Technique in the Transverse Wave Approach for the EM-Modeling of Fractal-Like Tree Structure used in 5G Applications," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13216–13221, Apr. 2024, https://doi.org/10.48084/etasr.6744.

[2] G. Goel and A. K. Chaturvedi, "Multi-Objective Load-balancing Strategy for Fog-driven Patient-Centric Smart Healthcare System in a Smart City," *Engineering, Technology & Applied Science Research*, vol. 14, no. 4, pp. 16011–16019, Aug. 2024, https://doi.org/10.48084/etasr.7749.

[3] A. G. Putrada, M. Abdurohman, D. Perdana, and H. H. Nuha, "EdgeSL: Edge-Computing Architecture on Smart Lighting Control With Distilled KNN for Optimum Processing Time," *IEEE Access*, vol. 11, pp. 64697–64712, 2023, https://doi.org/10.1109/ACCESS.2023.3288425.

[4] A. Badshah, A. Daud, M. Alhajlah, T. Alsahfi, B. Alshemaimri, and G. Ur-Rehman, "Smart Cities' Big Data: Performance and Cost Optimization With Regional Computing," *IEEE Access*, vol. 12, pp. 128896–128908, 2024, https://doi.org/10.1109/ACCESS.2024.3457269.

[5] J. Li, C. Gu, Y. Xiang, and F. Li, "Edge-cloud Computing Systems for Smart Grid: State-of-the-art, Architecture, and Applications," *Journal of Modern Power Systems and Clean Energy*, vol. 10, no. 4, pp. 805–817, Jul. 2022, https://doi.org/10.35833/MPCE.2021.000161.

[6] L. Zeng, X. Chen, P. Huang, K. Luo, X. Zhang, and Z. Zhou, "Serving Graph Neural Networks With Distributed Fog Servers for Smart IoT Services," *IEEE/ACM Transactions on Networking*, vol. 32, no. 1, pp. 550–565, Feb. 2024, https://doi.org/10.1109/TNET.2023.3293052.

[7] C. Núñez-Gómez, B. Caminero, and C. Carrión, "HIDRA: A Distributed Blockchain-Based Architecture for Fog/Edge Computing Environments," *IEEE Access*, vol. 9, pp. 75231–75251, 2021, https://doi.org/10.1109/ACCESS.2021.3082197.

[8] Y. Zhang, C.-Y. Wang, and H.-Y. Wei, "Parking Reservation Auction for Parked Vehicle Assistance in Vehicular Fog Computing," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 4, pp. 3126–3139, Apr. 2019, https://doi.org/10.1109/TVT.2019.2899887.

[9] M. Mukherjee, L. Shu, and D. Wang, "Survey of Fog Computing: Fundamental, Network Applications, and Research Challenges," *IEEE Communications Surveys & Tutorials*, vol. 20, no. 3, pp. 1826–1857, 2018, https://doi.org/10.1109/COMST.2018.2814571.

[10] Y. Yang, K. Wang, G. Zhang, X. Chen, X. Luo, and M.-T. Zhou, "MEETS: Maximal Energy Efficient Task Scheduling in Homogeneous Fog Networks," *IEEE Internet of Things Journal*, vol. 5, no. 5, pp. 4076–4087, Oct. 2018, https://doi.org/10.1109/JIOT.2018.2846644.

[11] C. Lin, G. Han, X. Qi, M. Guizani, and L. Shu, "A Distributed Mobile Fog Computing Scheme for Mobile Delay-Sensitive Applications in SDN-Enabled Vehicular Networks," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 5, pp. 5481–5493, May 2020, https://doi.org/10.1109/TVT.2020.2980934.

[12] O. O. Ajibola, T. E. H. El-Gorashi, and J. M. H. Elmirghani, "Disaggregation for Energy Efficient Fog in Future 6G Networks," *IEEE Transactions on Green Communications and Networking*, vol. 6, no. 3, pp. 1697–1722, Sep. 2022, https://doi.org/10.1109/TGCN.2022.3160397.

[13] K. Mishra, G. N. V. Rajareddy, U. Ghugar, G. S. Chhabra, and A. H. Gandomi, "A Collaborative Computation and Offloading for Compute-Intensive and Latency-Sensitive Dependency-Aware Tasks in Dew-Enabled Vehicular Fog Computing: A Federated Deep Q-Learning Approach," *IEEE Transactions on Network and Service Management*, vol. 20, no. 4, pp. 4600–4614, Dec. 2023, https://doi.org/10.1109/TNSM.2023.3282795.

[14] M. R. Rezaee, N. A. W. Abdul Hamid, M. Hussin, and Z. A. Zukarnain, "Fog Offloading and Task Management in IoT-Fog-Cloud Environment: Review of Algorithms, Networks, and SDN Application," *IEEE Access*, vol. 12, pp. 39058–39080, 2024, https://doi.org/10.1109/ACCESS.2024.3375368.

[15] H. B. Mahesh, A. Ali, S. M. Usha, and S. Mallikarjunaswamy, "Optimized Efficiency of IoT-Based Next Generation Smart Wireless Sensor Networks Using a Machine Learning Algorithm," *International Journal of Computing and Digital Systems*, vol. 18, no. 1, pp. 1–10, Apr. 2025, https://doi.org/10.12785/ijcds/1571107237.

[16] M. Poornima, T. N. Anitha, S. Mallikarjunaswamy, and M. L. Umashankar, "An efficient internet of things based intrusion detection and optimization algorithm for smart networks," *International Journal of Computing and Digital Systems*, vol. 17, no. 1, pp. 1–12, Jan. 2025, https://doi.org/10.12785/ijcds/1571001227.

[17] P. M. Urs, A. T. N. Reddy, S. Mallikarjunaswamy, and U. M. Lakshminarayan, "An Innovative IoT Framework using Machine Learning for Predicting Information Loss at the Data Link Layer in Smart Networks," *Engineering, Technology & Applied Science Research*, vol. 15, no. 2, pp. 20904–20911, Apr. 2025, https://doi.org/10.48084/etasr.9597.

[18] Z. Wei, B. Li, R. Zhang, and X. Cheng, "Contract-Based Charging Protocol for Electric Vehicles With Vehicular Fog Computing: An Integrated Charging and Computing Perspective," *IEEE Internet of Things Journal*, vol. 10, no. 9, pp. 7667–7680, May 2023, https://doi.org/10.1109/JIOT.2022.3182163.

[19] R. Vohnout *et al.*, "Living Lab Long-Term Sustainability in Hybrid Access Positive Energy Districts—A Prosumager Smart Fog Computing Perspective," *IEEE Internet of Things Journal*, vol. 10, no. 21, pp. 18898–18908, Nov. 2023, https://doi.org/10.1109/JIOT.2023.3280594.

[20] G. Proietti Mattia and R. Beraldi, "Online Decentralized Scheduling in Fog Computing for Smart Cities Based on Reinforcement Learning," *IEEE Transactions on Cognitive Communications and Networking*, vol. 10, no. 4, pp. 1551–1565, Aug. 2024, https://doi.org/10.1109/TCCN.2024.3378219.

[21] R. Kumar and N. Agrawal, "EDMA-RM: An Event-Driven and Mobility-Aware Resource Management Framework for Green IoT-Edge-Fog-Cloud Networks," *IEEE Sensors Journal*, vol. 24, no. 14, pp. 23004–23012, Jul. 2024, https://doi.org/10.1109/JSEN.2024.3404470.

[22] F. Guim *et al.*, "Autonomous Lifecycle Management for Resource-Efficient Workload Orchestration for Green Edge Computing," *IEEE Transactions on Green Communications and Networking*, vol. 6, no. 1, pp. 571–582, Mar. 2022, https://doi.org/10.1109/TGCN.2021.3127531.

[23] A. Rafiq, W. Ping, W. Min, and M. S. A. Muthanna, "Fog Assisted 6TiSCH Tri-Layer Network Architecture for Adaptive Scheduling and Energy-Efficient Offloading Using Rank-Based Q-Learning in Smart Industries," *IEEE Sensors Journal*, vol. 21, no. 22, pp. 25489–25507, Nov. 2021, https://doi.org/10.1109/JSEN.2021.3058976.


AUTHORS PROFILE

**Mrs. Nandini Gowda Puttaswamy** is currently working as Asst. Professor in Information Science and Engineering, Sapthagiri College of Engineering, Bangalore. She completed her B.E. in CSE from VTU, M.Tech. in Software Engineering from VTU and is pursuing Ph.D. from Visvesvaraya Technological University. She has published around 4 papers in National Conference and her area of research interest is Cloud Computing, Fog Computing, Edge Computing and IoT, AI, ML, Big Data Analytics. Google Scholar ID: CVKruXIAAAAJ, ORCID ID: 0009-0008-2909-2259

**Dr. Anitha Narasimha Murthy** is currently working as Professor in Computer Science and Engineering, BNM Institute of Technology, Bangalore. She completed her B.E. in CSE from Bangalore University, M.Tech. in Information Technology from Bangalore University and Ph.D. from Visvesvaraya Technological University. She has published around 30 research papers and her area of research interest is AI, ML, Big Data Analytics, Data Mining. Google Scholar ID: oN56OGwAAAAJ&hl, ORCID ID: 0000-0001-6162-8481, Scopus ID: 57205543659.