International Journal of Innovative Computer Science and IT Research

Volume 02, Issue 01 – Jan-Feb 2026 • E-ISSN: 3067-1108 | P-ISSN: 3067-1094

Autonomous IoT Systems for Adaptive Resource Management

Dr. Lucas E. Pereira

Professor, Federal University of Minas Gerais, Brazil

Abstract

The rapid proliferation of Internet of Things (IoT) devices has created increasingly complex computing environments in which large numbers of heterogeneous sensors, actuators, gateways, and intelligent devices continuously consume and generate computational, communication, storage, and energy resources. Conventional resource-management mechanisms frequently rely on static allocation policies or centralized control, making them less effective when IoT workloads and network conditions change dynamically. Autonomous IoT systems provide an alternative approach by incorporating intelligent monitoring, adaptive decision-making, automated resource allocation, and self-optimization capabilities. This research examines autonomous IoT systems designed for adaptive resource management and analyzes their architectural components, decision-making processes, resource allocation mechanisms, and operational challenges. The study adopts a conceptual and analytical methodology to investigate how sensing, monitoring, prediction, optimization, and feedback mechanisms can be integrated into IoT environments.

Particular attention is given to computational resources, communication bandwidth, storage, energy consumption, and service availability. The analysis demonstrates that autonomous resource management can improve resource utilization by continuously adapting allocation decisions according to workload intensity, device conditions, application requirements, and network characteristics. Distributed intelligence can further reduce dependence on centralized controllers and support faster responses in geographically distributed IoT environments. However, challenges involving interoperability, computational limitations, security, scalability, decision accuracy, and coordination overhead remain important barriers to practical deployment.

The proposed architectural perspective integrates IoT devices, intelligent control mechanisms, edge or fog resources, and cloud services into an adaptive computing continuum. Such an architecture can support smart cities, industrial automation, intelligent transportation, healthcare monitoring, environmental sensing, and connected infrastructure. The findings indicate that autonomous IoT systems can significantly strengthen the flexibility and efficiency of resource management when supported by predictive analytics, intelligent orchestration, decentralized decision-making, and continuous feedback. Future research should focus on explainable autonomous management, reinforcement learning, collaborative intelligence, energy-aware optimization, and secure self-adaptive IoT architectures.

Keywords: Autonomous IoT, Internet of Things, Adaptive Resource Management, Intelligent Systems, Resource Allocation, Edge Computing, Fog Computing, Machine Learning, Energy Optimization, Distributed Computing.

International Journal of Innovative Computer Science and IT Research

Volume 02, Issue 01 – Jan-Feb 2026 ● E-ISSN: 3067-1108 | P-ISSN: 3067-1094

1. Introduction

The Internet of Things has become a major computing paradigm by connecting physical devices, sensors, machines, vehicles, appliances, and infrastructure through communication networks. These devices continuously produce data and require computational, communication, storage, and energy resources to perform their functions. As IoT deployments expand, resource requirements become increasingly dynamic because workloads vary according to environmental conditions, application demand, device activity, and network availability. Traditional resource-management techniques based on predefined configurations may therefore fail to provide efficient resource utilization in highly dynamic IoT environments.

Autonomous IoT systems address this limitation by introducing intelligent mechanisms capable of monitoring system conditions, identifying resource requirements, making decisions, and automatically adapting operational configurations. Such systems aim to reduce the need for continuous human intervention while maintaining application performance. Autonomous capabilities can include self-configuration, self-optimization, self-healing, adaptive task scheduling, workload migration, and intelligent energy management. These capabilities are particularly relevant to large-scale IoT environments where manually managing every device and resource becomes impractical.

Adaptive resource management involves continuously adjusting available resources according to changing workload and system conditions. Computational capacity may be allocated among applications according to processing requirements, while communication bandwidth can be dynamically assigned based on traffic patterns. Storage resources may be reorganized according to data priority, and energy consumption can be optimized by adjusting device activity or computation placement. These adaptive mechanisms enable IoT systems to maintain service quality while avoiding unnecessary resource consumption.

The integration of edge and fog computing further strengthens autonomous resource management. Instead of transferring all IoT workloads to centralized cloud platforms, computational tasks can be processed closer to data-generating devices. Edge and fog nodes can monitor local conditions, perform preliminary analytics, and make time-sensitive allocation decisions. Cloud infrastructure can provide large-scale computational resources and centralized analytics when required. This distributed model creates a computing continuum in which resources can be dynamically selected according to latency, workload, energy, and application requirements.

The objective of this research is to examine autonomous IoT systems for adaptive resource management and analyze their ability to dynamically allocate and optimize heterogeneous resources. The study evaluates architectural components, intelligent management mechanisms, resource optimization strategies, and major implementation challenges. It further identifies future research opportunities involving artificial intelligence, predictive resource management, distributed decision-making, and secure autonomous operation.

2. Objectives

2.1 Primary Objective

The primary objective of this research is to examine autonomous IoT architectures capable of dynamically monitoring, allocating, and optimizing computational, communication, storage, and energy resources according to changing workloads, environmental conditions, network characteristics, and application-level requirements.

Volume 02, Issue 01 – Jan-Feb 2026 ● E-ISSN: 3067-1108 | P-ISSN: 3067-1094

2.2 Intelligent Resource Allocation

The first objective is to investigate intelligent mechanisms for dynamically allocating IoT resources. The study examines how machine learning, predictive analytics, optimization algorithms, and automated orchestration can identify changing resource requirements. Adaptive allocation is considered important for preventing resource underutilization and overload. The objective also includes examining how autonomous systems can distribute tasks among IoT devices, edge nodes, fog infrastructure, and cloud platforms according to operational requirements.

2.3 Performance and Energy Optimization

The second objective is to analyze how autonomous resource-management mechanisms can improve system performance while reducing unnecessary energy consumption. The study considers processing latency, bandwidth utilization, computational workload, storage efficiency, and device energy requirements. Adaptive mechanisms are examined for their ability to respond to workload fluctuations and maintain service quality. Energy-aware resource allocation is particularly emphasized for battery-powered IoT devices operating in distributed environments.

2.4 Reliability and Autonomous Operation

The third objective is to examine the role of autonomous decision-making in improving reliability, scalability, and operational continuity. IoT systems should detect resource shortages, network disruptions, and device failures and respond without requiring constant human intervention. The study therefore evaluates self-monitoring, self-optimization, task migration, fault recovery, and adaptive configuration mechanisms as important components of resilient autonomous IoT environments.

3. Review of Literature

3.1 Autonomous Internet of Things

Autonomous IoT represents an evolution from conventional connected-device architectures toward systems capable of making operational decisions with limited human intervention. Autonomous systems integrate sensing, communication, analytics, and intelligent control to respond to changing conditions. Their capabilities may include automatic configuration, workload adaptation, anomaly detection, and service optimization. Such capabilities become increasingly important as IoT environments grow beyond the scale that can be effectively controlled through centralized management.

Artificial intelligence and machine learning provide important foundations for autonomous IoT operation. Learning algorithms can analyze historical and real-time data to identify resource-demand patterns and predict future requirements. Intelligent decision mechanisms can then determine appropriate resource allocation strategies. However, models must operate within the computational and energy constraints of IoT environments, requiring lightweight algorithms and efficient distributed learning approaches.

3.2 Adaptive Resource Management

Resource management in IoT involves the allocation and coordination of heterogeneous resources across devices, gateways, edge systems, fog nodes, and cloud platforms. Static resource allocation can be inefficient because IoT workloads are often unpredictable. Adaptive management addresses this problem

Volume 02, Issue 01 – Jan-Feb 2026 ● E-ISSN: 3067-1108 | P-ISSN: 3067-1094

by continuously monitoring system conditions and modifying resource assignments according to current requirements.

Optimization techniques have been applied to workload scheduling, computation offloading, bandwidth allocation, and energy management. Multi-objective optimization is particularly important because IoT systems must often balance competing requirements. For example, reducing latency may increase energy consumption, while minimizing energy use may reduce computational performance. Autonomous systems therefore require decision mechanisms capable of balancing multiple objectives simultaneously.

3.3 Edge Intelligence and Distributed Decision-Making

Edge and fog computing provide an important foundation for autonomous IoT resource management because they place computational resources closer to IoT devices. Local decision-making can reduce communication latency and enable faster resource adaptation. Edge intelligence can process sensor information and determine whether tasks should be executed locally, transferred to nearby resources, or sent to centralized cloud infrastructure.

Distributed decision-making also improves resilience by reducing dependence on a single management controller. Multiple intelligent nodes can independently monitor local environments while coordinating with neighboring nodes when necessary. However, decentralized operation introduces challenges involving synchronization, trust, coordination overhead, and consistency. Effective autonomous IoT architectures must therefore balance local autonomy with global coordination.

4. Methodology

4.1 Research Design

This study adopts a conceptual and analytical research design to investigate autonomous IoT systems and their adaptive resource-management capabilities. The methodology focuses on identifying relationships among IoT devices, resource-monitoring mechanisms, intelligent decision engines, edge/fog infrastructure, and cloud services. The analysis considers resource availability, workload variation, latency, energy consumption, communication requirements, and service quality as major evaluation dimensions.

A layered architectural model is used to analyze how autonomous resource-management decisions can be generated and executed. IoT devices provide operational data, monitoring components assess resource conditions, and intelligent management mechanisms determine appropriate actions. Edge and fog resources provide localized processing, while cloud platforms support large-scale analytics and storage. Continuous feedback between these layers enables iterative adaptation of resource allocation decisions.

4.2 Autonomous Resource Monitoring

Resource monitoring is considered the first operational stage of autonomous management. The proposed analytical framework monitors CPU utilization, memory consumption, storage availability, communication bandwidth, energy level, workload intensity, and service status. Continuous monitoring provides the information required for identifying resource shortages and predicting potential performance degradation.

Volume 02, Issue 01 – Jan-Feb 2026 • E-ISSN: 3067-1108 | P-ISSN: 3067-1094

Monitoring mechanisms should operate with limited overhead because excessive monitoring can itself consume computational and communication resources. Therefore, adaptive monitoring frequency can be used according to workload criticality and system conditions. High-priority applications may require continuous monitoring, whereas less sensitive workloads can be monitored periodically. This approach supports efficient observation while preserving available resources for application execution.

4.3 Intelligent Decision-Making and Allocation

The decision-making layer analyzes monitoring information and determines how resources should be allocated. Machine learning models, optimization algorithms, rule-based mechanisms, and reinforcement learning can be used to identify appropriate resource-management actions. Decisions may involve task scheduling, computation offloading, resource scaling, workload migration, or bandwidth redistribution.
The analytical framework considers multiple resource-management objectives simultaneously.

These include:

- Minimizing processing latency
- Reducing unnecessary energy consumption
- Balancing computational workloads
- Improving bandwidth utilization
- Maintaining application quality of service
- Preventing resource overload
- Supporting device and service scalability
- Increasing operational reliability

Autonomous decisions are continuously evaluated through system feedback. If an allocation decision does not produce the expected outcome, the management layer can modify the strategy and select another resource configuration.

4.4 Feedback, Adaptation, and Performance Evaluation

Feedback mechanisms provide the basis for continuous adaptation. After resources are allocated, system performance is monitored to determine whether the selected configuration satisfies application requirements. Indicators such as latency, energy consumption, throughput, resource utilization, and task completion status can be compared with predefined performance objectives.

Performance evaluation considers both technical efficiency and operational stability. A resource-management strategy should not improve one metric while creating unacceptable degradation in another. Therefore, adaptive management is analyzed as a multi-objective process. The framework emphasizes continuous learning, dynamic adjustment, and feedback-driven optimization to maintain stable operation under changing IoT conditions.

5. Analysis

5.1 Adaptive Resource Management Architecture

An autonomous IoT resource-management architecture can be organized into interconnected layers. The device layer generates operational data and consumes resources, while the monitoring layer observes system conditions. The intelligence layer analyzes resource requirements and selects appropriate actions. Edge and fog resources execute time-sensitive workloads, while cloud infrastructure provides scalable processing and storage.

Volume 02, Issue 01 – Jan-Feb 2026 ● E-ISSN: 3067-1108 | P-ISSN: 3067-1094

This architecture enables autonomous resource allocation through a continuous monitoring-decision-action-feedback cycle. When workload intensity changes, the system can detect the change and dynamically redistribute resources. Similarly, when energy availability decreases, workloads can be migrated or computation can be reduced to preserve device operation.

Table 1: Functional Components of an Autonomous IoT Resource-Management Architecture

Architectural Component	Primary Function	Adaptive Capability
IoT Devices	Data generation and sensing	Adjust operational activity
Monitoring Layer	Resource and status observation	Dynamic monitoring
Intelligence Layer	Decision generation	Predictive and adaptive decisions
Edge/Fog Layer	Local computation	Task placement and migration
Network Layer	Data communication	Dynamic bandwidth allocation
Cloud Layer	Large-scale processing	Elastic resource provisioning
Feedback Layer	Performance assessment	Continuous optimization
Security Layer	Protection and authentication	Adaptive threat response

Interpretation: Table 1 shows that autonomous resource management requires cooperation among multiple architectural components. The intelligence and feedback layers are particularly important because they transform monitoring information into adaptive actions. Edge and fog infrastructure provides localized execution capabilities, while cloud resources support large-scale workloads. This layered organization enables resource decisions to be continuously adjusted according to changing operational conditions.

5.2 Resource Optimization Dimensions

Autonomous resource management must consider multiple resource categories simultaneously. Computational resources determine how quickly workloads can be executed, while network resources influence communication efficiency. Storage resources determine the ability to retain generated data, and energy resources directly affect the operational lifetime of many IoT devices.

A multi-objective strategy is therefore more suitable than optimizing a single performance indicator. For example, minimizing latency alone could result in aggressive use of computational resources and increased energy consumption. An autonomous system should instead determine a balanced allocation strategy based on application priorities and current system conditions.

Volume 02, Issue 01 – Jan-Feb 2026 • E-ISSN: 3067-1108 | P-ISSN: 3067-1094

Table 2: Adaptive Resource Management Strategies for IoT Environments

Resource Type	Adaptive Management Strategy	Expected Outcome
CPU	Dynamic task scheduling	Improved processing efficiency
Memory	Workload-aware allocation	Reduced memory contention
Storage	Data prioritization and caching	Efficient storage utilization
Bandwidth	Traffic-aware allocation	Reduced congestion
Energy	Energy-aware computation	Extended device lifetime
Computing Location	Dynamic offloading	Reduced latency
Network Connectivity	Adaptive routing	Improved reliability
Application Services	Dynamic scaling	Stable service quality
Fog/Edge Nodes	Workload balancing	Reduced node overload
Cloud Resources	Elastic provisioning	Scalable computation

Interpretation: Table 2 demonstrates that autonomous management can address several resource categories simultaneously. Dynamic task scheduling, workload balancing, computation offloading, and energy-aware management can collectively improve IoT performance. The effectiveness of these mechanisms depends on accurate monitoring and intelligent decision-making. Adaptive strategies should therefore be coordinated rather than independently applied to individual resource categories.

5.3 Performance and Operational Implications

The analysis indicates that autonomous resource management can improve the responsiveness and efficiency of distributed IoT systems by continuously adjusting resources according to workload conditions. Instead of maintaining fixed resource configurations, autonomous mechanisms can increase resources during high-demand periods and reduce unnecessary allocation during low-demand periods.

Another important implication is improved operational resilience. Autonomous systems can detect overloaded nodes, unavailable resources, or changing connectivity and automatically modify task placement. This reduces dependence on manual intervention and enables IoT applications to continue operating under changing environmental and network conditions.

6. Discussion

6.1 Intelligent and Predictive Resource Allocation

Autonomous IoT systems can move resource management from reactive approaches toward predictive management. Historical workload information and real-time sensor data can be analyzed to estimate future resource requirements. Predictive models can then prepare computational or communication resources before demand increases, reducing the likelihood of performance degradation.

Machine learning-based allocation can also identify complex relationships among workload, energy consumption, network conditions, and application requirements. However, predictive decisions

Volume 02, Issue 01 – Jan-Feb 2026 ● E-ISSN: 3067-1108 | P-ISSN: 3067-1094

must remain adaptable because IoT environments may experience unexpected events. Continuous feedback and model updating are therefore essential for maintaining decision accuracy.

6.2 Energy-Aware Autonomous Management

Energy is a critical resource in IoT systems, particularly for battery-powered sensors and mobile devices. Autonomous resource management can reduce energy consumption through adaptive duty cycling, workload migration, computation offloading, and intelligent communication scheduling. Systems can prioritize essential tasks while reducing resource consumption for non-critical operations.

Energy-aware management should also consider the computational cost of intelligence itself. Complex machine learning models may require significant processing resources. Consequently, autonomous architectures should use lightweight models where appropriate and determine whether intelligent processing should occur locally, at an edge node, or within the cloud.

6.3 Reliability and Self-Management

Autonomous systems can improve reliability by continuously monitoring system conditions and responding to failures or performance anomalies. A self-managing IoT infrastructure can identify overloaded resources, communication failures, or abnormal device behavior and initiate corrective actions. This capability is valuable for critical applications where prolonged service interruption may create operational risks.

Self-management also supports scalability. As new devices are added, autonomous mechanisms can identify available resources and integrate devices into the existing infrastructure. Automated configuration and service discovery can reduce administrative effort. Nevertheless, autonomous actions must be governed by secure policies to prevent incorrect or malicious decisions.

7. Challenges

Autonomous IoT resource management faces substantial challenges associated with device heterogeneity and resource constraints. IoT devices differ considerably in processing capability, memory, energy availability, communication protocols, and operating environments. Developing a common management strategy that performs effectively across such diverse devices is difficult. Furthermore, resource monitoring and intelligent decision-making require computational overhead. If management mechanisms consume excessive resources, the expected efficiency benefits may be reduced.

Security and trust represent additional challenges because autonomous systems are capable of making operational decisions without continuous human supervision. A compromised device, malicious fog node, or manipulated monitoring signal could influence resource-allocation decisions. Secure authentication, data integrity verification, access control, and trustworthy decision mechanisms are therefore essential. Autonomous systems should also provide mechanisms for detecting abnormal behavior and preventing unauthorized changes to resource-management policies.

Scalability and coordination become increasingly difficult as IoT deployments grow. A centralized autonomous controller may become a bottleneck when managing very large numbers of devices. Fully decentralized management can reduce this dependency but may introduce synchronization and coordination problems. Dynamic environments involving mobile devices create further complexity

Volume 02, Issue 01 – Jan-Feb 2026 ● E-ISSN: 3067-1108 | P-ISSN: 3067-1094

because resource availability and network connectivity can change rapidly. Efficient service migration and adaptive workload placement are therefore necessary for maintaining continuous operation.

8. Future Research

Future research should investigate reinforcement learning and deep reinforcement learning for autonomous resource management. These approaches can enable IoT systems to learn allocation strategies through continuous interaction with their environments. Research should focus on developing lightweight learning models capable of operating under limited computational and energy resources. Multi-agent reinforcement learning may also support cooperation among distributed IoT and edge nodes while reducing dependence on centralized controllers.

Another promising research direction involves explainable autonomous resource management. As IoT systems increasingly make operational decisions automatically, administrators need to understand why particular resources were allocated or workloads were migrated. Explainable artificial intelligence could improve transparency and trust in autonomous systems. Research should also investigate human-in-the-loop mechanisms that allow administrators to define high-level policies while permitting autonomous systems to manage routine operational decisions.

Future studies should further explore secure, energy-aware, and self-healing IoT architectures. Federated learning could allow distributed devices and edge nodes to collaboratively improve resource-management models without sharing sensitive raw data. Digital twins could provide virtual representations of IoT infrastructure for testing allocation strategies before deployment. Integration with edge, fog, and cloud computing should also be investigated to create adaptive computing continua capable of dynamically selecting the most appropriate processing location.

9. Conclusion

Autonomous IoT systems represent an important advancement in the management of increasingly complex and heterogeneous Internet of Things environments. The rapid expansion of connected devices has created significant demands for computational capacity, communication bandwidth, storage, and energy, while resource requirements continuously change according to workload intensity, application priorities, environmental conditions, and network availability. Conventional static management approaches are often unable to respond efficiently to these variations. The analysis presented in this research demonstrates that autonomous resource management can address these limitations by integrating continuous monitoring, intelligent decision-making, dynamic allocation, and feedback-driven adaptation. Through these capabilities, IoT systems can automatically adjust resource configurations according to changing operational requirements. The integration of edge and fog computing further strengthens this model by enabling resource decisions and computational tasks to be performed closer to data-generating devices.

The study also demonstrates that effective autonomous resource management requires a coordinated approach to multiple resource dimensions. Computational capacity, memory, storage, network bandwidth, energy, and service availability should not be optimized independently because changes in one resource can influence the requirements of others. Multi-objective management strategies can balance latency, energy efficiency, throughput, resource utilization, and quality of service. Intelligent scheduling and computation offloading can distribute workloads according to current conditions, while adaptive bandwidth allocation and energy-aware strategies can improve operational

efficiency. Autonomous systems can additionally support self-configuration, self-optimization, service migration, and fault recovery, thereby reducing the need for continuous manual intervention. However, the deployment of such systems remains challenging because of device heterogeneity, limited resources, security vulnerabilities, coordination requirements, and the complexity of autonomous decision-making. These issues demonstrate the need for architectures that combine intelligent adaptation with strong governance, security, and reliability mechanisms.

Future development should focus on creating autonomous IoT infrastructures that are predictive, explainable, secure, energy-aware, and capable of continuous learning. Reinforcement learning, federated learning, multi-agent intelligence, digital twins, and intelligent edge orchestration can provide new mechanisms for improving autonomous resource allocation. At the same time, lightweight algorithms are required to ensure that the computational cost of intelligence does not exceed the benefits obtained from optimization. Secure identity management, trustworthy decision processes, and adaptive anomaly detection will be necessary to protect autonomous systems against manipulation. The integration of IoT devices with edge, fog, and cloud infrastructures can establish a flexible computing continuum in which workloads dynamically move according to application requirements and resource conditions. Overall, autonomous resource management provides a promising foundation for developing scalable, responsive, and efficient IoT ecosystems capable of operating intelligently under dynamic real-world conditions.

References

1. Atzori, L., Iera, A., & Morabito, G. (2010). The Internet of Things: A survey. *Computer Networks*, 54(15), 2787–2805.
2. Gubbi, J., Buyya, R., Marusic, S., & Palaniswami, M. (2013). Internet of Things: A vision, architectural elements, and future directions. *Future Generation Computer Systems*, 29(7), 1645–1660.
3. Bonomi, F., Milito, R., Zhu, J., & Addepalli, S. (2012). Fog computing and its role in the Internet of Things. *Proceedings of the First Edition of the MCC Workshop on Mobile Cloud Computing*, 13–16.
4. Chiang, M., & Zhang, T. (2016). Fog and IoT: An overview of research opportunities. *IEEE Internet of Things Journal*, 3(6), 854–864.
5. Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing: Vision and challenges. *IEEE Internet of Things Journal*, 3(5), 637–646.
6. Satyanarayanan, M. (2017). The emergence of edge computing. *Computer*, 50(1), 30–39.
7. Yousefpour, A., Ishigaki, G., & Jue, J. P. (2018). Fog computing: Towards minimizing application delay in the Internet of Things. *IEEE Internet of Things Journal*, 5(2), 817–829.
8. Mouradian, C., Naboulsi, D., Yangui, S., Glitho, R. H., Morrow, M. J., & Polakos, P. A. (2018). A comprehensive survey on fog computing: State-of-the-art and research challenges. *IEEE Communications Surveys & Tutorials*, 20(1), 416–464.
9. Al-Fuqaha, A., Guizani, M., Mohammadi, M., Aledhari, M., & Ayyash, M. (2015). Internet of Things: A survey on enabling technologies, protocols, and applications. *IEEE Communications Surveys & Tutorials*, 17(4), 2347–2376.
10. Xu, L. D., He, W., & Li, S. (2014). Internet of Things in industries: A survey. *IEEE Transactions on Industrial Informatics*, 10(4), 2233–2243.

11. Zanella, A., Bui, N., Castellani, A., Vangelista, L., & Zorzi, M. (2014). Internet of Things for smart cities. *IEEE Internet of Things Journal*, 1(1), 22–32.
12. Roman, R., Lopez, J., & Mambo, M. (2018). Mobile edge computing, fog et al.: A survey and analysis of security threats and challenges. *Future Generation Computer Systems*, 78, 680–698.
13. Dastjerdi, A. V., & Buyya, R. (2016). Fog computing: Helping the Internet of Things realize its potential. *Computer*, 49(8), 112–116.
14. Yi, S., Li, C., & Li, Q. (2015). A survey of fog computing: Concepts, applications and issues. *Proceedings of the 2015 Workshop on Mobile Big Data*, 37–42.
15. Hu, P., Dhelim, S., Ning, H., & Qiu, T. (2017). Survey on fog computing: Architecture, key technologies, applications and open issues. *Journal of Network and Computer Applications*, 98, 27–42.
16. Mach, P., & Becvar, Z. (2017). Mobile edge computing: A survey on architecture and computation offloading. *IEEE Communications Surveys & Tutorials*, 19(3), 1628–1656.
17. Abbas, N., Zhang, Y., Taherkordi, A., & Skeie, T. (2018). Mobile edge computing: A survey. *IEEE Internet of Things Journal*, 5(1), 450–465.
18. Shi, W., & Dustdar, S. (2016). The promise of edge computing. *Computer*, 49(5), 78–81.
19. Varghese, B., & Buyya, R. (2018). Next generation cloud computing: New trends and research directions. *Future Generation Computer Systems*, 79, 849–861.
20. Bellavista, P., Berrocal, J., Corradi, A., Das, S. K., Foschini, L., & Zanni, A. (2019). A survey on fog computing for the Internet of Things. *Pervasive and Mobile Computing*, 55, 71–83.
21. Yousefpour, A., Fung, C., Nguyen, T., Kadiyala, K., Jalali, F., Niakanlahiji, A., Kong, J., & Jue, J. P. (2019). All one needs to know about fog computing and related edge computing paradigms. *IEEE Communications Surveys & Tutorials*, 21(1), 111–154.