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Artificial Intelligence: The Sea That IoT, SDN and Cloud Computing Sail On

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ABSTRACT

Artificial intelligence (AI) has emerged as a cornerstone in the realm of information technology, reshaping industries with its promise of enhanced services and efficiency. As companies navigate a landscape driven by modernity, decisiveness, security, and insights, AI's inherent capabilities are pivotal. Technologies such as cloud computing, the Internet of Things (IoT), and software-defined networking (SDN) stand at the forefront, promising transformative applications for society. By integrating AI with these innovations, scalability reaches new heights, propelling efficiency to unprecedented levels. The influx of data from diverse devices undergoes a cycle of reception, exchange, storage, management, and analysis, driving automation and performance optimization while ensuring reliability. Yet, despite their promise, these technologies encounter limitations. The synthesis of AI with cloud, IoT, and SDN presents both challenges and opportunities, particularly concerning scalability and reliability. This paper delves into the role of AI in addressing these issues, highlighting the opportunities for research to bridge current gaps and chart future directions in ensuring the seamless integration and advancement of these transformative technologies.

Keywords:

Artificial intelligence, Cloud computing, IoT, Reliability, Scalability, Software-defined networking

I. INTRODUCTION

Artificial intelligence (AI) has emerged as a transformative force, reshaping every significant aspect of computing and innovation. With its ability to learn from prior experiences and operate autonomously, AI is revolutionizing diverse domains. Once perceived as rigid and esoteric, AI has evolved into a flexible tool deployed across various fields [1]. Despite its vast potential, current AI applications only scratch the surface of what it can achieve. AI's reasoning capabilities drive advancements by analyzing historical data, identifying patterns, and facilitating real-time decision-making. By automating processes and minimizing errors, AI enhances efficiency and augments human intelligence.

Industry 4.0 emphasizes the development of "smart factories" through automation [2]. In the information technology landscape, innovations like cloud computing, the Internet of Things (IoT), and software-defined networking (SDN) wield significant influence, contributing to enhanced productivity levels. Figure 1 illustrates the array of technologies supporting Industry

4.0, underscoring the pivotal role of AI in this ecosystem. Leveraging knowledge, understanding, and decision-making capabilities, AI propels cognitive intelligence, driving the transition toward smarter industries. Cloud services coupled with IoT devices, tailored to individual user preferences, are poised to deliver optimal performance. The heterogeneity of devices necessitates interoperability, fostering scalability, reliability, and improved user satisfaction.

In this context, reliability denotes the consistent delivery of joint services, reflecting the system's trustworthiness and susceptibility to failure. Scalability, on the other hand, refers to the system's capacity to accommodate increasing demands efficiently. It encompasses the ability to manage rising demand loads without compromising quality attributes [4]. As the integration of AI with cloud computing, IoT, and SDN progresses, ensuring scalability and reliability becomes paramount. This paper explores the challenges and opportunities inherent in this integration, guiding researchers toward addressing current gaps and charting future directions.

Figure 1. Technologies supporting Industry 4.0

The interdependency between reliability and scalability underscores the challenge of resource allocation in interconnected systems. As the number of connected devices increases, resource starvation can compromise reliability, while an excess of unused resources arises from fewer connections. AI's predictive capabilities offer a solution by anticipating resource needs in advance, optimizing utilization. Despite ongoing research into integrating AI with cloud computing, IoT, and SDN, the performance assessment of these integrations remains elusive, particularly concerning scalability and reliability.

AI has catalyzed advancements across various technological domains, including cloud computing, IoT, and SDN [5]. While numerous metrics gauge performance, reliability, and scalability hold paramount importance. Although individual studies have addressed reliability and scalability within each technology, the integration of these technologies with AI remains relatively unexplored. This paper proposes common reliability and scalability testing attributes applicable to cloud computing, IoT, and SDN. It examines AI's role in mitigating challenges within each technology and outlines future directions for their integration.

The subsequent sections delve into further detail:

Section 2 reviews related literature.

Section 3 outlines reliability and scalability testing attributes.

Section 4 explores reliability and scalability in AI-enabled cloud computing, IoT, and SDN.

Section 5 identifies research challenges and opportunities in integrating these technologies.

Finally, **Section 6** concludes the discussion.

II. RELATED LITERATURE

Various scholars have extensively researched the convergence of technologies, shedding light on pertinent challenges and proposing innovative solutions. Reddy [6] delves into the integration challenges of IoT with wireless sensor networks, highlighting concerns surrounding security, software, and hardware. However, the assessment attributes for such integration remain unexplored. In the transition to smart industries, AlEnezi [7] identifies different challenges across countries, emphasizing mindscaping, investment, and security and privacy as key hurdles. Addressing the efficiency of low-power IoT devices, Sharma [8] proposes fog node controllers within a scalable IoT networking framework, leveraging blockchain-based distributed cloud architecture and SDN to ensure usability, real-time data transmission, scalability, and stability.

Gill and Buyya [9] discuss open issues in cloud services, including failure management, workload distribution, and accountability, proposing a conceptual model to match user requirements with reliable services dynamically. Hohlfeld [10] focuses on SDN's role in IoT communication, highlighting scalability challenges in data, control, and application planes, particularly in traffic monitoring and security. Sharafeddine and Farhat [11] present a heuristic approach to enhance communication reliability and device scalability, optimizing cluster head selection for lower failure costs.

In the realm of smart grids, [12] proposes an anomaly detection technique using symbolic dynamic filters and dynamic Bayesian networks to differentiate between faults, disturbances, and cyber-attacks, ensuring reliable power distribution amidst potential threats. Big flow [13] challenges the efficacy of machine learning-based intrusion detection in high-speed networks, proposing a verification model for scalable, accurate detection.

Rao et al. [14] advocate homomorphic encryption for enhanced cloud-consumer communication security, while Plantevin et al. [15] introduce an intelligent transducer architecture for smart homes, ensuring reliable communication and scalability at a minimal cost.

Though reliability and scalability assessment attributes vary across technologies, commonalities exist, necessitating a comprehensive approach to evaluation.

III. RELIABILITY AND SCALABILITY ATTRIBUTES

The attributes employed to evaluate reliability and scalability are closely intertwined, with their dependability often interlinked. Figure 2 illustrates the comprehensive list of attributes utilized for testing reliability and scalability. System reliability pertains to its ability to consistently meet customer service requirements amidst various mitigating factors and market volume fluctuations [16]. Assessing system reliability entails navigating a multifaceted landscape characterized by universality, heterogeneity, and uncertainty. Table 1 elaborates on the attributes employed for testing reliability, encapsulating the diverse facets of system performance and dependability.

Figure 2. Reliability and scalability testing attributes

Table 1. Reliability testing attributes

Attribute	Explanation
Data Consistency	The extent to which all the data items on a scale measure one construct making the data consistent on all the devices. Consistency in data leads to better reliability.
Stability	The results obtained using an instrument should be consistent on repeated testing to ensure stability. And a highly stable system ensures reliability.
Equivalence	Coherence between the responses of different device consumers or between the alternative type of devices proves equivalence. Equivalence increases reliability.
Interoperability	Through sharing data in a common standard format, the chosen device software will communicate with on-site applications to allow the devices to interoperate.
Security	The efficiency of data must be evaluated by the various organizations like NIST, COBIT and ISACA to ensure security. The security is the most significant attribute as any security breach may result in catastrophic incidences.
Usability	The usability term applies to the degree to which a particular form of the customer may utilize a device, service or program to accomplish the final target with performance, efficiency and reliability while interacting with various categories of computing devices.
Availability	Through sharing data in a common standard format, the chosen device software will communicate with on-site applications to allow the devices to interoperate.

In a centralized environment, scalability emerges as a critical concern. Scalability denotes the capacity to enhance the distribution capability of computing services by augmenting the volume of data processed [17]. It involves the dynamic provisioning and de-provisioning of devices to accommodate fluctuating demands. Scalability characterizes the network load distribution as services are allocated, with scalable systems exhibiting a linear increase in loading slope proportional to resource expansion. Conversely, systems that do not scale efficiently display a flattening of this curve. Scalability is gauged by assessing the segment between two units, achieving maximum capacity with minimal deployment. Table 2 elucidates the attributes pertinent to testing scalability, encompassing various facets crucial for evaluating system performance under increasing loads and resource allocations.

IV. ROLE OF ARTIFICIAL INTELLIGENCE IN CLOUD COMPUTING, IOT AND SDN

The emerging technologies discussed in this paper present a myriad of challenges that demand attention. AI emerges as a pivotal player in tackling these challenges head-on. Drawing from related literature studies, this paper synthesizes key challenges encountered within each technology, as depicted in Figure 3.

A. Role of AI in cloud computing

The integration of cloud computing into various online activities is already underway [18], reshaping the landscape of information technology (IT) across industries. The fusion of AI with cloud computing is driving significant transformations, revolutionizing the way businesses leverage IT solutions [19]. Examples like Siri and Amazon Alexa illustrate how AI-powered assistants have become integral parts of daily life, epitomizing the seamless integration of AI into cloud-based platforms. This integration empowers the cloud to function as an AI-driven self-management system, where AI algorithms analyze data to optimize repetitive tasks within IT systems. By learning from past experiences, AI enhances the reliability of cloud services, enabling efficient processing and manipulation of vast datasets.

Moreover, AI-driven automation streamlines data collection processes, ensuring the delivery of accurate information to customers while flagging any abnormal behavior promptly. Deep neural network models facilitate intelligent analysis, providing enterprises with enhanced data control and real-time insights. This heightened data management capability not only improves reliability but also enhances the overall user experience.

The advent of AI-powered tools like Salesforce's Einstein [20] further illustrates the synergy between AI and cloud computing. By translating customer data into actionable insights, Einstein enhances sales strategies and customer interactions, leveraging various social networking channels. This integration fosters a more dynamic and personalized approach to software-as-a-service (SaaS), augmenting customer engagement and driving business growth.

Table 2. Scalability testing attributes

Attribute	Explanation
Resource management	Resources are very crucial and should be used efficiently and effectively. The increase in resources increases the capacity of handling the load but the deallocation of resources should not affect the performance of the system much. So, effective resource management supports the system in terms of scalability.
Response time	The time from which the request has been made to the time the request started processing is said to be response time. When a greater number of devices start using the same resource then the response time decreases as the new requests will be waiting in the queue.
Throughput	The number of requests processed in a unit of time is called throughput. When multiple devices share a common resource then the throughput decreases as the resource time has to be shared among all the devices.
Latency	Latency is the time delay taken to respond to the request. Latency can be due to setup time or communication time too.
CPU usage	CPU is a very scarce resource and should be used very efficiently. When the scalability increases the CPU usage also increases as a greater number of devices tend to use it. At the same time, the devices connected should not fall below or exceed the threshold to have better CPU usage.
Memory usage	Increase in scalability occupies more memory. The devices information and the data from the devices are stored in the memory. High scalability results in more memory usage.
Network usage	The devices are connected in a network and communicate with each other. The network usage is determined by the link utilization between the devices. Increase in scalability increases network usage.

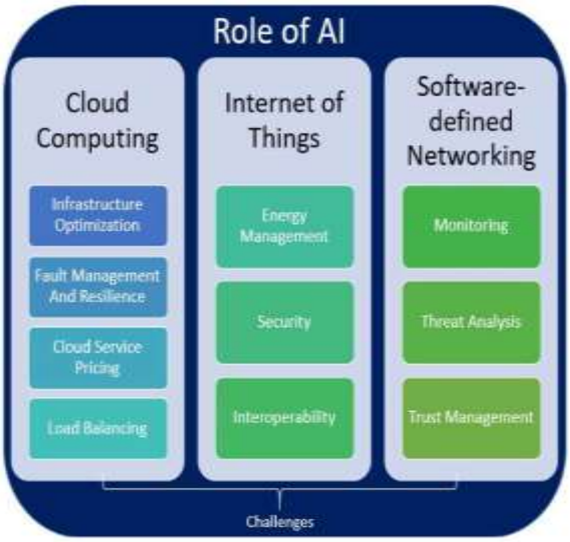

Figure 3. Role of AI in addressing challenges

In addition to the services offered by the cloud to consumers, the concept of artificial intelligence-as-a-service (AIaaS) [21] has gained prominence, providing users with access to various AI technologies such as neural networks and machine learning. These technologies leverage vast datasets to construct, train, process, and execute models effectively, making analysis, calculations, and workload statistics more accessible across cloud servers. By intelligently utilizing cloud resources, which can dynamically scale up or down based on demand, manual processing of large volumes of data is minimized, reducing consumer loss over time. Moreover, artificial intelligence significantly bolsters fault tolerance mechanisms [22], facilitating the detection and handling of application malfunctions through server relocations and leveraging supervised and unsupervised deep learning approaches to identify and mitigate loss trends.

The integration of AI into cloud computing aims to democratize access to AI technologies by anchoring cloud infrastructure with AI applications through continuous integration, continuous delivery, and phased deployments. Authors in [23] proposed a framework called model ops for reliable and trusted AI-based cloud lifecycle management to mitigate deployment risks, although resource management limitations under large-scale use cases remain unaddressed. Software architects are actively developing reliable and scalable cloud-assisted smart factories that integrate various AI technologies, fostering logical relationships between different AI components. As AI continues to advance, there is speculation that private and public clouds may increasingly rely on AI resources for monitoring, control, and self-healing in the event of issues. Table 3 highlights some of the major challenges in cloud computing related to reliability and scalability, along with the role of AI in addressing them.

Table 3. Role of AI in addressing the challenges in cloud computing

Major challenges in cloud computing	Role of AI in providing a solution
Infrastructure optimization	Neural networks and fuzzy systems can be used for classification of operating status. Machine language can be used for extracting the data from previous instances. Evolutionary computing can be used for multi-objective optimization.
Fault management and Resilience	Neural networks, fuzzy systems and evolutionary computing can be used for mapping the tasks to the virtual machines. Neural networks, fuzzy systems and machine learning can be used for prediction of the faults.
Cloud service pricing	Neural networks, fuzzy systems and machine learning can be used for predicting market price trend and user demand. Neural networks can be used for mapping cost and demand for a price. Evolutionary computing can be used for multi-objective optimization.
Load balancing	Neural networks can be used for detecting load imbalance and for mapping virtual machines and dependability issues. Fuzzy systems can be used for specifying preferences, constraints, and management guidelines. Evolutionary computing can be used for multi-objective optimization.

B. Role of AI in the internet of things

The Internet of Things (IoT) encompasses a network of interconnected objects that autonomously capture, share, and utilize data, revolutionizing various aspects of daily life [24]. This seamless exchange of information between IoT devices enhances operational efficiency but also generates vast volumes of data, necessitating the intervention of artificial intelligence (AI) algorithms to capture and process this data effectively. By leveraging AI algorithms, IoT devices can derive actionable insights from the data, thereby improving their functionality and utility. The integration of AI with IoT applications is particularly relevant in areas such as the industrial Internet of Things (IIoT) and the consumer Internet of Things (CIoT), as depicted in Figure 4.

For instance, in [25], the IoT plays a pivotal role in delivering patient information to doctors, facilitating sustainable development in the healthcare sector. Moreover, IoT technologies are extending their reach into smart cities, smart homes, and smart buildings, where automation and energy consumption optimization are primary concerns [26]. Researchers are actively addressing these challenges to enhance user satisfaction [27].

The growing demand for comfort among communities has led to increased information sharing among IoT devices, resulting in higher energy consumption and heat generation. While traditional techniques exist to control household energy consumption, frameworks like the one proposed in [28] utilize feed-forward backpropagation neural networks to predict household energy consumption accurately, automating the process and ensuring reliability. In the realm of IoT communication, ensuring reliability is crucial, especially under low-power, long-range (LoRa) limitations. In [29], B. Reynders focuses on LoRa wide-area networks (LoRaWAN) and proposes a two-step lightweight scheduling approach to enhance reliability and scalability. By dynamically evaluating each channel's transmission power and spreading factors, nodes can make informed decisions to improve reliability while maintaining scalability through attributes like throughput and packet error ratio.

In the realm of IoT, security emerges as a significant concern due to the interconnected and scalable nature of heterogeneous networks. This interconnectedness increases the vulnerability of IoT systems to various bugs and cyber-attacks, posing a risk to critical operations. Moreover, the integration of big data with network and social data amplifies these security concerns, as different modes such as physical, cyber, and social media (PCS) converge, creating complex attack surfaces. Artificial intelligence (AI) plays a crucial role in addressing these security challenges by enabling users to counter a range of attack styles, as outlined in [30].

Table 4 outlines some of the major challenges in IoT related to ensuring reliability and supporting scalability, along with the pivotal role of AI in providing solutions to mitigate these challenges.

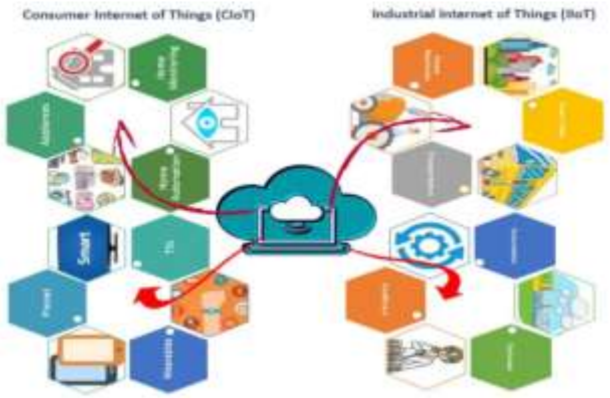

Figure 4. Consumer and Industrial IoT

Table 4. Role of AI in addressing the challenges in IoT

Major challenges in IoT	Role of AI in providing a solution
Energy management	Neural networks and fuzzy systems can be used for energy consumption prediction.
	Neural networks can be used for classifying energy usage.
	Machine language can be used for extracting the data from previous instances.
Security	Neural networks, fuzzy systems and machine learning can be used for classification and clustering of security patterns in intrusion detection and malware detection.
Interoperability	Fuzzy systems can be used for defining the matching preferences by specifying the constraints.
	Machine learning can be used for extracting knowledge from previous instances.
	Neural networks can be used for mapping the tasks.
	Neural networks and fuzzy systems can be used for prediction of workload.

C. Role of AI in Software-defined networking

Software-defined networking (SDN) represents a significant breakthrough in advancing network architectures to the next generation [31]. By refining fine-grained flow management, SDN enables more robust network configurations through the decoupling of the control plane and data plane, providing a centralized view of the network with enhanced flexibility. Its deployment across various domains such as corporate networks, data centers, and internet sharing centers has facilitated the transition from conventional networking to SDN architecture, albeit with scalability challenges due to potential switch flow data explosion.

The centralized control afforded by SDN simplifies network functionality but raises scalability concerns, particularly regarding the control plane's ability to handle virtualization-induced complexities. Furthermore, SDN's concept of isolating the control plane and data plane from switches promotes interoperability among networking components from different vendors. However, this softwarization of networking within the three layers of SDN presents reliability challenges, alongside issues like scalability, efficiency, consistency, interoperability, and security.

To address these challenges, artificial intelligence (AI) complements SDN by overcoming scalability, efficiency, and security concerns. For instance, the gated recurrent neural network (GRU-RNN) model [33] detects intrusions, enhancing system reliability by minimizing error gradients and tracking network component activities. SDN reliability hinges on data plane, control path, and control plane reliability, with various solutions proposed by authors to enhance reliability and scalability.

Table 5. Role of AI in addressing the challenges in SDN

Major challenges in SDN	Role of AI in providing a solution
Monitoring	Fuzzy systems can be used for specifying behaviour patterns and constraints. Neural networks, Fuzzy systems and machine learning can be used for detecting behaviour anomalies.
Threat analysis	Neural networks, fuzzy systems and machine learning can be used for threat detection and analysis.
Trust management	Neural networks, fuzzy systems and machine learning can be used for trust classification and behaviour.

D. Role of AI in the fusion

The convergence of emerging technologies like cloud computing, IoT, and SDN with artificial intelligence (AI) is poised to revolutionize the landscape of information technology, surpassing conventional boundaries and ushering in a new era of innovation [35]. SDN, in particular, emerges as a potent platform to enhance the scalability and versatility of IoT devices via the cloud, leveraging advancements in communication technologies such as 5G to overcome networking challenges.

AI enhances efficiency across various applications, amplifying its impact when integrated with cloud computing, IoT, and SDN. As depicted in Figure 5, the convergence of these technologies promises enhanced results individually and collectively across a diverse range of applications. By fusing AI with cloud, IoT, and SDN, societies can streamline digital operations and meet the demands of Industry 4.0. The concept of Artificial Intelligence Software-Defined Cloud of Things (AISDCoT) enables intelligent use of communication devices, secure data transmission, and implementation of SDN standards for efficient data storage and access.

Various AI techniques provide tailored solutions for issues within each technology domain, demonstrating their effectiveness in selection, allocation, mapping, and optimization. Fuzzy systems, for instance, define matching preferences and constraints in the cloud and IoT, ensuring reliability through classification and clustering of security patterns. Neural networks facilitate task mapping in the cloud, load imbalance detection, and energy usage classification in IoT devices, supporting scalability and dependability.

The interconnection of devices and communication with the cloud leverages SDN's networking capabilities, enabling vendor-free interactions and multi-objective optimization through evolutionary computing. Machine learning, as a subset of AI, extracts knowledge from past data to predict future occurrences, enhancing service reliability and scalability. Figure 6 illustrates the interaction between these technologies, showcasing AI's pivotal role in delivering reliable services through scalable devices, thereby demonstrating the feasibility of their integration.

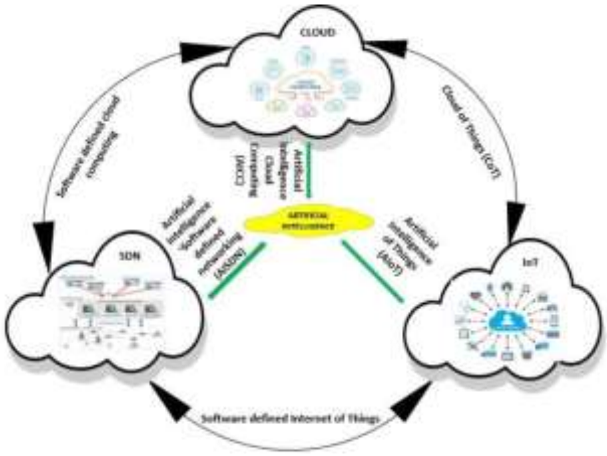

Figure 5. Artificial intelligence software-defined cloud of things (AISDCoT) [36]

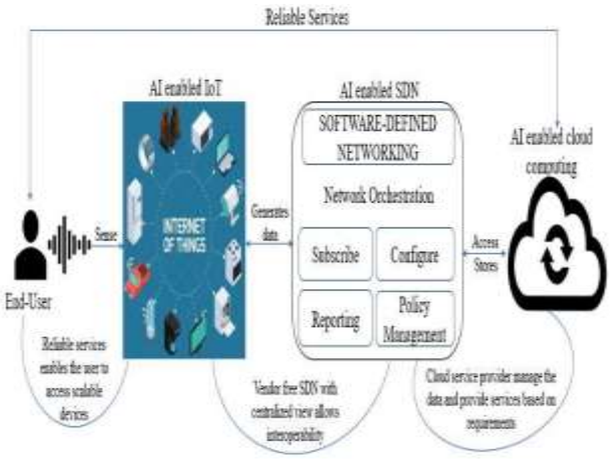

Figure 6. Reliability and scalability from the end-user's perspective

V. FUTURE DIRECTIONS AND OPEN ISSUES

In the pursuit of providing highly reliable and scalable services to end-users, it's imperative to address various challenges and explore future research directions to enhance the fusion of the aforementioned technologies. Here are some key areas for future exploration:

a. Security: The scalability of devices in networks introduces vulnerabilities if new devices are added or removed without proper authentication. Future research could focus on developing AI techniques to authenticate devices and prevent different types of attacks, enhancing overall security.

b. Interaction: Improving interactions within IoT networks via SDN requires efficient transmission protocols and applications. Future research could explore the use of AI-capable techniques to design protocols and applications that meet end-user requirements effectively.

c. Communication Management: Managing communication among devices over large geographical areas necessitates flexible monitoring and management systems. Future research could investigate AI-based traffic control and management systems to support reliable communication among a vast number of devices.

d. Flow Table Update: Frequent updates to SDN flow tables result in overhead and unreliability. Future research could develop AI-based mechanisms to predict flow table entries and removals, enhancing device scalability and reliability.

e. Interoperability: Lack of universal standards for device interoperability hinders quality of service. Future research could focus on developing intelligent and comprehensive technologies to address interoperability issues at all stages of communication.

f. Single Point Failure: SDN's complex network environments introduce challenges related to single point failures. Future research could explore AI-enabled techniques to predict and prevent such failures, ensuring network continuity.

g. Programming: Design failures in SDN controllers may lead to network inefficiencies and failures. Future research could develop efficient programs using AI techniques to identify and predict failures based on past experiences.

h. Load Balancing: Dynamic load allocation in wireless sensor networks using SDN interfaces requires efficient algorithms. Future research could develop customized AI algorithms to improve load balancing and enhance quality of service.

i. Resource Management: Optimal resource management is crucial for service efficiency. Future research could explore AI techniques to improve resource management and enhance service assessment metrics.

j. Energy Efficiency: Regulating heat pollution from devices is essential for achieving green computing. Future research could focus on developing AI interventions to conserve energy and reduce energy consumption when necessary, addressing the challenge of heat generated by machines.

Addressing these future research directions will contribute to advancing the reliability and scalability of the integration of cloud computing, IoT, SDN, and AI, paving the way for more efficient and resilient technological ecosystems.

VI. CONCLUSION

This paper delves into the pivotal role of AI in the realms of cloud computing, IoT, and SDN, shedding light on the integration of AI with these cutting-edge technologies. It highlights several issues concerning this integration, given the current advancements in these fields. With the widespread application of AI methods, systems can operate intelligently with minimal human intervention when coupled with appropriate patterns and theories.

The paper discusses the testing attributes used to evaluate the reliability and scalability performance of these integrated systems, along with exploring how AI addresses the associated challenges in cloud computing, IoT, and SDN, both individually and collectively. Moreover, it outlines future directions and open issues to consider while amalgamating these technologies.

However, it's worth noting that certain crucial aspects such as training data issues, deployment challenges, and computing performance have not been thoroughly addressed in the integration process. Addressing these complexities will not only resolve the common issues encountered in this fusion but also tackle individual development problems across these phenomena.

Ultimately, this study serves as a valuable resource for consumers and researchers looking to delve deeper into the integration of these technologies. By identifying and addressing the challenges associated with this fusion, it lays the groundwork for future research endeavors and advancements in these application combinations.

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