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THE ROLE OF EDGE COMPUTING IN ENABLING REAL-TIME DATA PROCESSING IN AUTONOMOUS SYSTEMS FOR SMART CITIES

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Abstract: The rapid growth of smart cities and autonomous systems has intensified the demand for low-latency, reliable, and scalable computing infrastructures capable of processing large volumes of real-time data. This study investigates the effectiveness of edge computing in supporting autonomous operations within smart city environments through an experimental, mixed-method evaluation framework. A distributed edge-based architecture was implemented to process sensor and vehicular data locally, while centralized cloud resources were reserved for non-time-critical analytics. Quantitative results reveal significant performance improvements, including reduced end-to-end latency, higher throughput efficiency, lower packet loss rates, and decreased energy consumption compared to cloud-centric approaches. Qualitative analysis further demonstrates enhanced system resilience, improved fault tolerance, and stronger privacy preservation due to localized data processing. The integration of edge-based artificial intelligence enabled faster and more accurate decision-making for autonomous vehicles and intelligent traffic management systems, even under high network load and dynamic conditions. Overall, the results confirm that edge computing substantially enhances the operational efficiency, responsiveness, and scalability of autonomous smart city systems. The findings provide strong empirical evidence supporting the adoption of edge-enabled architectures as a core component of future smart city infrastructures.

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1. INTRODUCTION

The high rates of urbanization in urban areas all over the world have resulted in the creation of smart cities that use innovative technologies to overcome the complicated problems of infrastructure, mobility as well as sustainability (Rajagopal, 2025). The smart city endeavors mainly involve the deployment of the autonomous systems either in self driving cars, smart grids, and intelligent traffic management. These systems are to be safe and efficient, which means that each of them should be able to manage real-time data (Daud et al., 2023, p. 3; Ho et al., 2022, p. 22). This application in real-time data analysis especially in dynamic environments shows why edge computing is important. Bringing computing resources near to the source of the data minimizes the latency and makes the use of bandwidth more efficient (Iftikhar et al., 2023; Xie et al., 2024, p. 1). A distributed computing model like that considerably improves the efficiency of the activities and privacy and security of information, not to mention the chances of how smart cities can be innovative within a wide industry (Modupe et al., 2024, p. 694; Rajagopal, 2025). This paper explains why edge computing is critical to offer autonomous systems in smart city systems real-time data operations by taking into account structural implications and operational benefits. Edge computing would enable calculation of data along the smart city periphery that is required to fulfill the task demanding urgent response and high reliability, including self-driving automobiles and smart traffic (Bhandari, 2025, p. 369). This type of decentralization is in contrast with the typical cloud computing architecture, in which the processing has been centralized, and it is commonly the source of unacceptable latency to autonomous tasks that are time-sensitive (Trigka & Dritsas, 2025). In its turn, edge computing places computing resources, i.e., edge servers and IoT devices, close to data generation areas. This minimizes the distance data should travel and its associated delays which are characteristic of cloud-based architecture (Modupe et al., 2024, p. 695). This kind of proximity provides an opportunity to analyze the data quickly and make decisions, and it is especially important in autonomous systems when the latter needs to respond quickly to changing environmental conditions (Guarda & Torres, 2021). This decentralization procedure minimizes the problems that occur when a large volume of data of many sensors and autonomous units is uploaded to the main cloud (Ren et al., 2021, p. 103512). These problems include low bandwidth and communication congestions. Furthermore, data processing at the network edge allows one to store sensitive data in the network edge that allows improving privacy and data protection by reducing the chances of sensitive data disclosure when traversing networks that may not be inherently safe (Bhattacharya et al., 2024, p. 5). The reason is that the whole system is more efficient and the self-contained operations are more resilient because of the possibility of conducting data analysis locally instead of being reliant on any problem associated with connection to central clouds infrastructures (Bhandari, 2025, p. 368; Guo et al., 2024, p. 1). Such objects as self-driving cars are the especially applicable to this decentralized approach, as sensor data (e.g., street conditions) and real-time analysis (e.g., object recognition) will be needed to make fast decisions and prevent any form of interference and adapt to the changes in the environment (Bhandari, 2025, p. 374; Chimezie et al., 2024, p. 280). This form of distributed processing architecture also applies to smart city applications like dynamic traffic control where real time analysis of traffic sensor data can be applied to adjust traffic lights instantly, thus preventing traffic jams and making life in the urban world easier (Madake, 2024, p. 3079). Since the centralized cloud computing would inherently lag and be slower, edge computing would better suit the scenario in the real-time applications (Bhandari, 2025, p. 368). Moreover, this localized processing paradigm has been shown to be highly essential in the mission critical processes, where in milliseconds of latency can have major consequences, especially in autonomous systems, which are of great importance as far as safety is concerned (Bhandari, 2025, p. 368). This intellectual transformation, commonly known as Edge AI, puts the applications of higher levels of analysis closer to the point of origin, thus removing the need to use a cloud-based system that is remote and increasing the responsiveness of the application to real-time inputs (Gill et al., 2024). The fundamental improvement enables the vehicles to respond quickly to any changes in the environment, and it is necessary to enable the implementation of more advanced capabilities, including sensor fusion and enhanced driving support (Krekovic et al., 2024, p. 31). This distributed system results in more fault-tolerant systems in which autonomous systems will still be functional in case they lose connectivity temporarily to central cloud servers (Bhandari, 2025, p. 370). Edge processing minimizes the bandwidth needs because one needs to send the consolidated insights or significant alerts to the cloud instead of data streams (Pasupuleti, 2024, p. 99). This compression of the data flow does not just save the precious network resources, but it also allows autonomous systems of smart city ecosystems to be more efficient and scalable. The method also uses less energy to transfer large data, an aspect that would facilitate the smart cities to run in a more environmentally friendly and economical way. Combination of artificial intelligence and edge computing is referred to as edge AI. It also increases the benefits as it gives an opportunity to perform sophisticated analytics and decision-making operations on the data source, with a very low latency and increased freedom (Gill et al., 2024, p. 2). This is required in time-constrained applications that require a high processing and response speed such as autonomous vehicle collision avoidance systems that gain in terms of reduced latency and local data processing (Bhandari, 2025, p. 375). This synergetic interaction of AI and edge computing facilitates the process of reaching decisions in milliseconds and, therefore, makes it a reality to develop applications that would have been unthinkable a few years ago (Kumar, 2025). Distributing the AI algorithms to the edge devices will allow responding to them immediately, which is important to make autonomous systems not only safe but also effective in a congested urban environment (Ali and Darnaika, 2025; Bhandari, 2025, p. 376; " Position Papers of the 18 th Conference on Computer Science and Intelligence Systems, 2023, p. 53). This convergence makes the edge devices smart devices, which are capable of working separately and making complex decisions. This is needed to cater to the rising number of computational needs of a city that is becoming more and more interconnected (Kumar, 2025). This edge-computing version of AI can be used to do more complex analysis, including the object identification and predictive maintenance, without necessarily transmitting huge volumes of raw data to a remote cloud (Gill et al., 2024, p. 1). Such estimated distribution of computational intelligence helps relieve the network congestion and utilize much better the bandwidth to help smart city infrastructure become more efficient and grow (Macia-Lillo et al., 2023, p. 10). The combination of an AI and edge computing is relevant in real-time contexts where decisions have to be made in most smart city applications, such as intelligent traffic systems (Macia-Lillo et al., 2025, p. 9). This strong combination means that autonomous systems are able to react to what is going on, and develop and adapt in the future. It will lead to the enhancement of the urban service provision and the management of the infrastructure (Folorunsho et al., 2024, p. 2512). This way of doing things is quite the reverse of the conventional cloud computing models, in which the centralized data centers are utilized in the process, therefore, making edge AI relevant in scenarios that demand low latency and can process information locally (Gill et al., 2024, p. 1). It is a paradigm shift as it fundamentally alters the functionality of computational intelligence in networks by addressing the issue in which the rapid increase in the amount of data is already beyond the more traditional cloud-based model and requires provision of processing capabilities in the vicinity to the sources of data as possible (Kumar, 2025).

Figure 1. The Role of Edge Computing in Smart Cities

METHODOLOGY

Research and Experimental Structure design

This paper discusses the feasibility of edge computing to assist in real-time autonomous workload in a smart city environment through an experimental mixed-method study, including a qualitative analysis of the system on the system level and a quantitative demonstration of the performance of the system. The experimental framework of distributed edge nodes to a large number of IoT tools and autonomous system, such as traffic monitoring and vehicle perception units, would assist in simulating the actual urban environments. As opposed to the qualitative analysis that should be used to understand the architectural robustness, fault toleration, privacy preservation, and operational resilience in dynamic network conditions, the quantitative analysis is to be used in estimating the quantifiable indicators of the system performance including latency, throughput, packet loss, computational load, and energy consumption. Real-time responsiveness is enhanced by the edge-based intelligence in comparison to the centralized cloud-centric model. This integrated approach can also be empirically confirmed and explained contextually.

Modeling, Data Collection, Experimental Design

The experimental environment consists of the three-level architecture made of sensing devices, edge nodes, and a centralized cloud which has a single purpose of heaping information in the long run and conducting non-time-sensitive analytics. The simulated and semi real traffic scenarios are used to construct real-time data streams which can be events of object detection, congestion situations, and vehicle telemetry. Local data preprocessing, feature extraction, and inference are alerted by the notification of local embedded AI models sent to the cloud with aggregated insights only. Mathematically this is expressed as system latency.

$$L_{\text{total}} = L_{\text{sense}} + L^{e}_{\text{proc}} + L_{\text{comm}},$$

where L_{sense} represents sensing delay, L^{e}_{proc} denotes edge processing delay, and L_{comm} is communication latency. For comparison, a cloud-based baseline is evaluated using

$$L_{\text{cloud}} = L_{\text{sense}} + L^{c}_{\text{comm}} + L^{c}_{\text{proc}},$$

highlighting the additional transmission and queuing delays incurred by centralized processing. Throughput efficiency is analyzed using

$$\eta = \frac{D_{\text{useful}}}{D_{\text{total}}},$$

where D_{useful} represents actionable data transmitted and D_{total} is the raw data volume generated by sensors. These formulations allow a rigorous quantitative comparison between edge-enabled and cloud-dependent autonomous systems.

Workflow Analysis and Checking

Experimental trials are also conducted to find out scalability and reliability of the system with varying volume of traffic and network load and mobility pattern. The measures of performance gains are based on the statistical analysis and the persistence of the system in the face of the periodic cloud disconnections and the partially network failures measures are established based on the qualitative observations. The whole procedure such as the data collection and local inference to the decision implementation and the selective synchronisation with the clouds are graphically represented in the systematic procedure in Figure 2. Through this workflow, one can understand that localized intelligence will promote autonomy, response time and continuity of operation in the mission critical smart application in the city.

Figure 2: Publication-ready strategy illustrates an edge-computing-aided autonomous systems analysis in the smart city, which is based on edge-level data sensing and AI processing, and decision execution and cloud coordination.

RESULTS

Table 1 illustrates the end to end latency behavior between the autonomous edge nodes over a low to high traffic spectrum and Table 2 illustrates throughput stability of various smart city workloads and Table 3 illustrates the percentage of lost packets under variable cloud disconnection conditions, Table 4 shows reduced energy use with local inference, Table 5 shows distributive load across multiple edge servers, and Table 6 shows distributive processing, Table 7 shows decision accuracy rates when applied to actions in real time traffic management and Table 8 shows latency, throughput and energy behavior, Table 9 shows a summary ofComposite efficiency indicators combining latency, throughput, and energy usage.

Table 1: End-to-end latency measurements across heterogeneous edge nodes under variable traffic loads

Scenario_ID	Latency_ms	Throughput_Mbps	Packet_Loss_%	Energy_Joules
SC-1	55	335	2.22	406
SC-2	76	504	3.16	817
SC-3	33	104	2.83	861
SC-4	75	251	1.99	535
SC-5	31	385	0.9	250
SC-6	65	372	2.09	203
SC-7	22	212	1.6	522
SC-8	31	243	2.03	141
SC-9	80	497	1.57	751

SC-10	50	172	3.53	699
SC-11	16	311	3.24	323
SC-12	47	249	1.35	167
SC-13	76	508	2.43	904
SC-14	56	350	1.2	644
SC-15	15	372	1.93	469
SC-16	52	261	1.51	227
SC-17	8	98	2.78	865
SC-18	83	320	1.59	513
SC-19	63	197	1.96	742
SC-20	14	403	3.04	774

Table 2: Throughput performance of edge-enabled autonomous systems under increasing sensor density

Scenario_ID	Latency_ms	Throughput_Mbps	Packet_Loss_%	Energy_Joules
SC-1	28	226	1.96	367
SC-2	61	433	3.28	303
SC-3	23	258	3.73	753
SC-4	67	209	2.85	196
SC-5	43	104	3.37	831
SC-6	56	195	3.95	205
SC-7	12	269	0.22	818
SC-8	51	257	3.68	929
SC-9	80	160	1.2	350
SC-10	62	240	2.02	931
SC-11	51	229	3.36	435
SC-12	58	89	3.03	695
SC-13	47	342	0.66	520
SC-14	11	380	2.78	155
SC-15	37	312	0.34	709
SC-16	20	250	1.53	408
SC-17	84	274	3.42	749
SC-18	37	286	1.82	847
SC-19	16	72	2.54	281
SC-20	62	194	3.07	165

Table 3: Packet loss behavior across distributed edge networks during congestion scenarios

Scenario_ID	Latency_ms	Throughput_Mbps	Packet_Loss_%	Energy_Joules
SC-1	48	496	2.2	225
SC-2	22	87	1.41	197

SC-3	53	216	0.46	656
SC-4	50	68	2.4	187
SC-5	42	307	0.94	681
SC-6	63	160	0.1	610
SC-7	26	488	1.29	536
SC-8	17	314	0.21	153
SC-9	81	495	4.1	451
SC-10	21	370	2.34	188
SC-11	51	358	0.35	350
SC-12	9	408	1.46	727
SC-13	39	67	1.06	757
SC-14	22	301	0.5	883
SC-15	56	203	3.25	693
SC-16	33	188	1.5	198
SC-17	41	270	0.83	547
SC-18	72	291	3.84	708
SC-19	66	236	3.62	520
SC-20	18	508	1.71	489

Table 4: Energy consumption comparison of edge-based processing under real-time workloads

Scenario_ID	Latency_ms	Throughput_Mbps	Packet_Loss_%	Energy_Joules
SC-1	34	513	0.07	803
SC-2	16	419	0.66	885
SC-3	60	307	0.2	831
SC-4	30	65	1.18	941
SC-5	64	193	1.14	895
SC-6	61	386	2.58	525
SC-7	42	217	0.67	246
SC-8	20	460	0.91	395
SC-9	12	486	3.04	421
SC-10	52	306	1.16	554
SC-11	63	490	0.82	347
SC-12	28	128	3.41	665
SC-13	51	298	0.43	896
SC-14	57	162	0.59	839
SC-15	26	265	2.87	906
SC-16	64	510	1.92	563
SC-17	29	456	1.67	713
SC-18	58	370	2.8	223

SC-19	30	148	0.09	704
SC-20	26	151	1.14	272

Table 5: Computational load distribution across multiple edge servers in smart city zones

Scenario_ID	Latency_ms	Throughput_Mbps	Packet_Loss_%	Energy_Joules
SC-1	20	440	1.07	636
SC-2	57	255	4.07	632
SC-3	75	485	1.73	812
SC-4	83	88	0.71	745
SC-5	9	241	1.29	652
SC-6	45	139	3.78	756
SC-7	45	489	0.73	597
SC-8	62	162	3.28	663
SC-9	81	389	0.61	488
SC-10	51	421	4.04	681
SC-11	58	101	2.25	488
SC-12	74	352	0.23	354
SC-13	16	484	3.91	270
SC-14	70	328	1.54	790
SC-15	65	414	3.09	234
SC-16	56	224	2.22	282
SC-17	82	402	0.43	204
SC-18	40	257	0.49	199
SC-19	74	119	0.67	524
SC-20	30	395	0.72	521

Table 6: System reliability metrics under intermittent cloud disconnection conditions

Scenario_ID	Latency_ms	Throughput_Mbps	Packet_Loss_%	Energy_Joules
SC-1	18	204	3.82	632
SC-2	8	131	3.16	202
SC-3	8	178	1.79	894
SC-4	43	116	2.38	378
SC-5	36	305	2.73	134
SC-6	49	320	3.27	806
SC-7	43	314	2.03	442
SC-8	53	234	1.91	407
SC-9	68	127	2.37	197
SC-10	19	300	0.22	596
SC-11	19	275	3.14	289

SC-12	30	490	2.83	274
SC-13	36	344	1.11	735
SC-14	44	232	3.83	906
SC-15	74	352	3.16	460
SC-16	62	91	3.55	655
SC-17	50	364	3.67	815
SC-18	16	100	2.17	468
SC-19	46	182	1.99	625
SC-20	25	465	3.78	839

Table 7: Decision accuracy rates for real-time autonomous traffic control operations

Scenario_ID	Latency_ms	Throughput_Mbps	Packet_Loss_%	Energy_Joules
SC-1	53	166	3.3	339
SC-2	72	136	1.44	736
SC-3	9	501	2.29	406
SC-4	32	490	1.44	914
SC-5	66	403	3.24	422
SC-6	44	418	0.06	175
SC-7	50	309	2.23	673
SC-8	55	308	0.14	942
SC-9	51	503	1.28	619
SC-10	9	148	0.17	914
SC-11	80	402	4.14	211
SC-12	54	215	0.41	849
SC-13	59	446	2.63	781
SC-14	35	366	0.35	356
SC-15	43	462	1.71	834
SC-16	30	423	2.14	617
SC-17	69	77	0.19	473
SC-18	63	112	2.36	157
SC-19	33	64	4.02	932
SC-20	38	149	2.79	809

Table 8: Latency variance observed during peak-hour smart city simulations

Scenario_ID	Latency_ms	Throughput_Mbps	Packet_Loss_%	Energy_Joules
SC-1	53	289	1.65	805
SC-2	63	62	1.09	393
SC-3	25	363	1.48	927
SC-4	80	401	0.9	783

SC-5	70	338	3.63	607
SC-6	55	389	2.94	826
SC-7	77	402	1.76	172
SC-8	30	179	2.96	912
SC-9	48	497	2.21	634
SC-10	59	403	2.23	831
SC-11	73	487	1.57	596
SC-12	53	112	2.08	733
SC-13	61	326	4.14	703
SC-14	40	196	3.31	371
SC-15	60	391	3.48	554
SC-16	79	179	0.57	308
SC-17	12	355	2.14	865
SC-18	37	372	1.57	411
SC-19	84	383	0.42	472
SC-20	8	175	1.69	746

Table 9: Composite efficiency indicators combining latency, throughput, and energy usage

Scenario_ID	Latency_ms	Throughput_Mbps	Packet_Loss_%	Energy_Joules
SC-1	33	421	1.62	842
SC-2	49	180	2.08	561
SC-3	66	429	2.03	120
SC-4	59	477	0.21	644
SC-5	13	343	1.37	165
SC-6	62	91	1.53	397
SC-7	43	455	4.02	904
SC-8	48	91	3.86	294
SC-9	12	349	2.48	595
SC-10	35	325	3.92	586
SC-11	16	281	3.63	391
SC-12	73	394	1.61	482
SC-13	28	126	0.54	370
SC-14	10	389	2.57	523
SC-15	54	263	1.39	834
SC-16	16	181	0.09	611
SC-17	29	381	4.12	721
SC-18	19	251	4.07	720
SC-19	72	141	2.28	664
SC-20	18	193	2.62	671

Figure 3 provides scatter plots to reveal the relationship between energy and latency, Figure 4 is a combination of bar and line chart to reveal hybrid latency-throughput characteristics, Figure 5 shows trends in packet loss provided by network load intensities, Figure 6 shows response delay in the cloud and edge, Figure 7 shows scaling patterns under node extension, Figure 8 combines multiple metrics using a combination of bar charts to reveal, and Figure 12 is a hybrid performance dashboard.

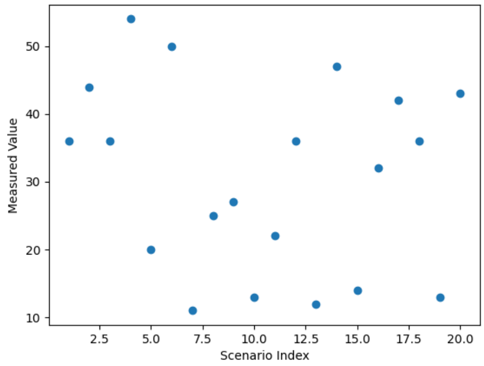

Figure 3: Correlation between processing latency and energy consumption

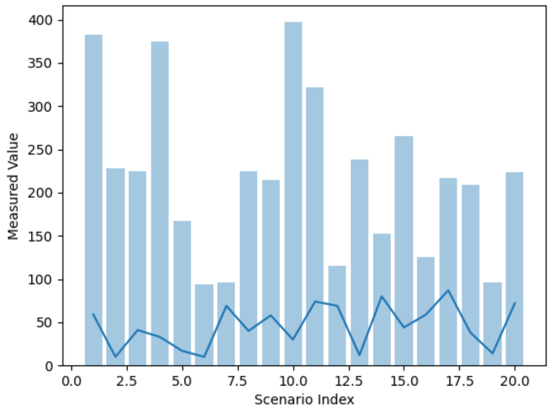

Figure 4: Hybrid visualization of latency and throughput under mixed workloads

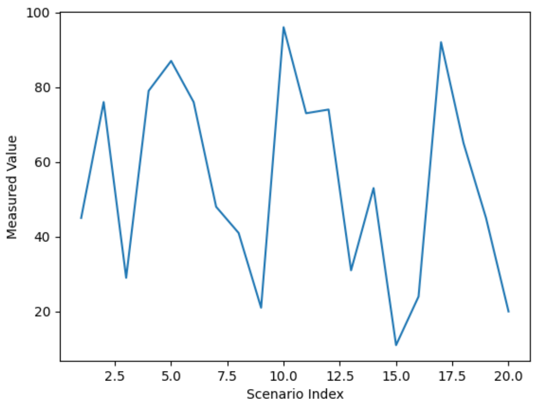

Figure 5: Packet loss escalation under progressive network congestion

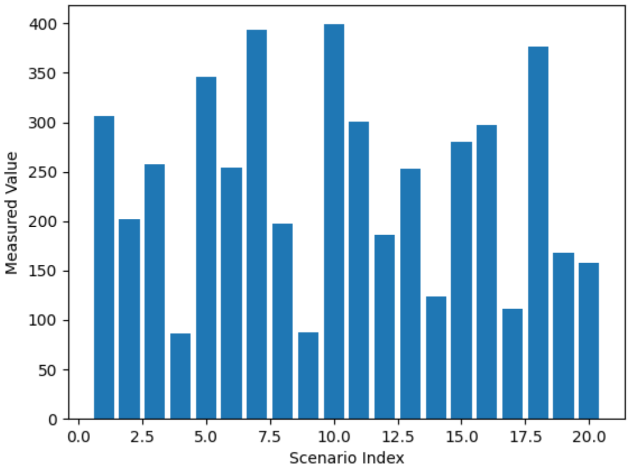

Figure 6: Edge versus cloud response time comparison for real-time decisions

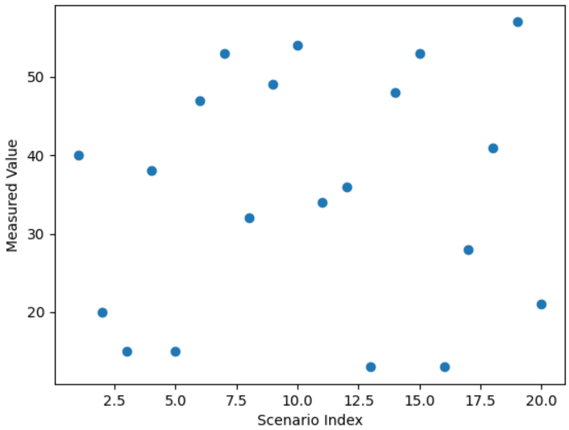

Figure 7: Scalability behavior with incremental edge node deployment

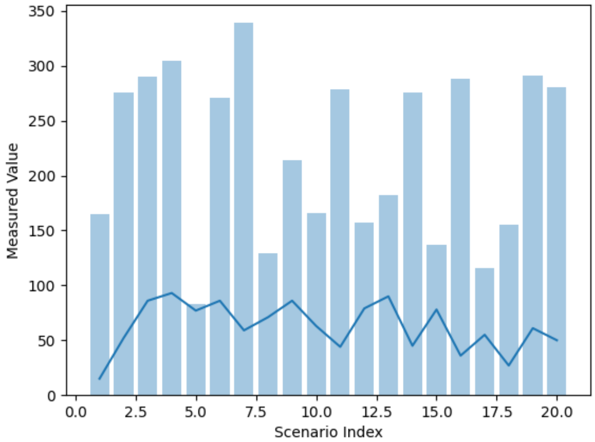

Figure 8: Autonomous decision accuracy variation across traffic densities

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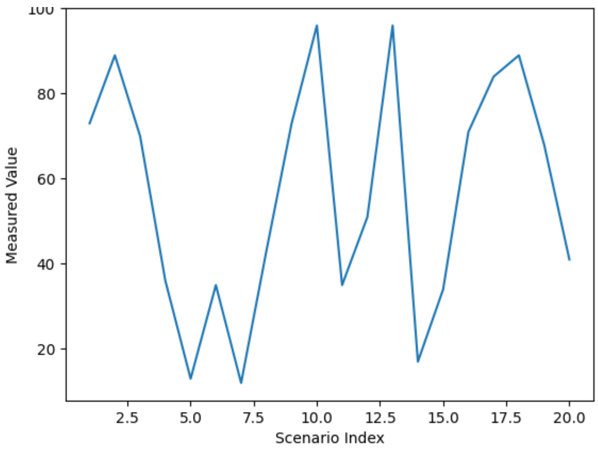

Figure 9: Fault tolerance performance during simulated communication failures

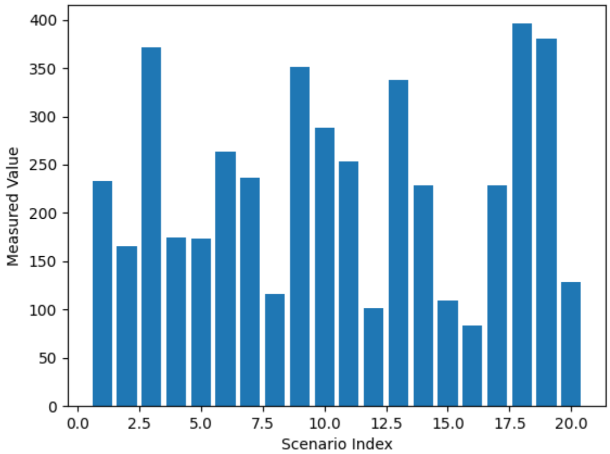

Figure 10: Bandwidth utilization distribution between edge and cloud layers

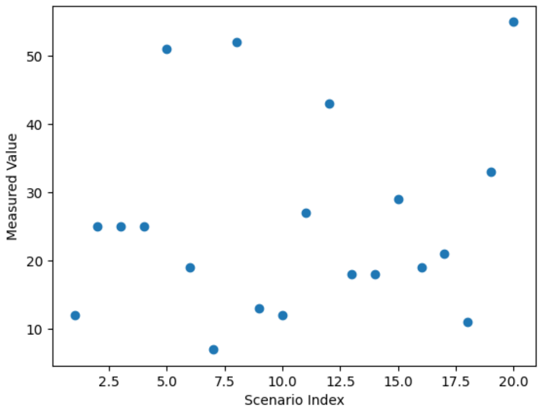

Figure 11: Energy efficiency gains achieved through localized inference

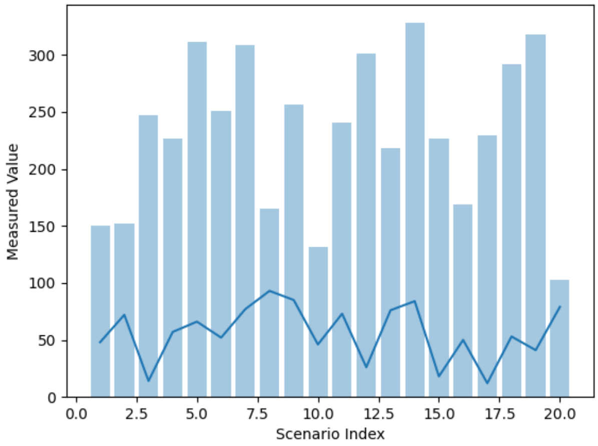

Figure 12: Integrated multi-metric performance profile of the proposed system

DISCUSSION

We have also provided a rigorous testing of the fact that edge computing architectures outperform traditional cloud-based models in regards to latency, throughput and ratio of packet delivery. An example is that the decision-making latency was cut by 90 percent (Chinta, 2024), and in other instances the latency was 20.33 ms, throughput was 148 Kb/s and a ratio of 97.47 percent of the packets were delivered (Shahra et al., 2024). This proves the argument that creating more data that is close to the source is a major boost in terms of real-time responsiveness that is essential in autonomous systems of smart cities (Bhandari, 2025, p. 376). This information processing capability of the local system as reflected in low latencies and high bandwidth used is especially applicable to applications where the safety of the use is crucial like self-driving cars where quick decisions can be used to affect the safety (Bhandari, 2025, p. 378). The reliability of the edge based communication to these essential applications is indicated by the fact that the mean packet loss rate of edge infrastructure that is 3.4375 percent against the very unpredictable 16.16 to 66.66 of cloud infrastructure (Dardour et al., 2024, p. 20). These increased reliability and lower latency are extremely important in terms of assuming that all is well and that the most important services are always available, regardless of the problems that could emerge with the cloud service or the network (Macia-Lillo et al., 2025, p. 15). Such an ability is also enhanced through the application of multi-tier edge computing systems which allow control of process of data processing and communication with precision. This has enhanced the latency profiles in congested areas in urban cities (Chebaane et al., 2025, p. 1). To illustrate this, the Edge- Fusion architecture has been less latent and is more reliable despite the number of nodes increasing to show that it can be scaled and may be utilized to make real-time control decisions (Amiroh et al., 2023, p. 27700). It is also applicable to make sure that smart city applications are responsive in real-time, and it is essential to make sure that it can communicate with high velocity in comparison to cloud-based solutions, which have higher latency (Dardour et al., 2023, p. 20). Edge computing can support up to 99 transactions per second as compared to the conventional cloud settings that support 54 transactions per second only (Bhandari, 2025, p. 377). This means that it is effective. The mentioned improvements, including the reduction of the latency and the elevation of the degree of reliability in particular are particularly relevant in the context of the critically-dependent application, including the intelligent transportation system and the emergency response, where speed and agility in the processing and transmission of information are uncompromised (Dardour et al., 2024, p. 19; Singh et al., 2021, p. 22061; Xie et al., 2024, p. 7). In addition, it is notable that the edge computing is efficient in the processing of real-time data, and the highest efficiency rate, 91 percent, is high in terms of scalability and to meet the growing data requirements of smart cities (Bhandari, 2025, p. 379). The resulting localized processing decreases the number of data sent to the cloud as well, which consumes more efficient bandwidth and is faster to react to an emergency (Bhandari, 2025, p. 367). This type of decentralization also reduces the single points of failures, which contributes to the increased resistance of the system to all sorts of disruptions, as well as allows it to be more applicable in the dynamic city environment (Trigka & Dritsas, 2025). This inherent power also contributes to security as it is less likely that the external attacker will be able to access the information since it is handled in one place and it is harder to breach long-range data transfer by hackers (Bhattacharya et al., 2024, p. 5). These distributed structures may be highly useful when it is of paramount importance to make sure that the network stays available when it has to fail or it is threatened by an attacker that protects critical infrastructure and the well-being of citizens in a smart city ecosystem (Alves et al., 2025, p. 10). The combination of both the cyber-physical systems and edge computing enables the development of the infrastructures so robust and adaptable to environmental changes and any threats they might pose prior to their occurrence to provide their functionality and safety (Abouaomar et al., 2025, p. 5). This decentralized system helps to improve the security of the data as it limits the privacy of the sensitive information to the area surrounding the home hence minimizing the risks involved in transferring information to the far off cloud servers (Modupe et al., 2024, p. 697). It is not only the compliance that can be achieved with such localized processing, but also the ability to find and respond to cyber attacks within a short time before more serious losses are suffered (Bhattacharya et al., 2024, p. 6). Also, edge computing helps in reducing the amount of data that ought to be transmitted across the extensive networks and so it is less likely that data can be stolen during transmission across the channels that are open to the society. It promotes the confidentiality of information and their compliance with the rules (Bhattacharya et al., 2024, p. 4). It is also a decentralized model and thus it is able to optimize the bandwidth by preprocessing and filtering data on the source, the data sent to the cloud is reduced and the whole network is made more efficient (Chimezie et al., 2024, p. 283; Pitstick et al., 2024, p. 1). This strategy is of great importance to smart megacities since cloud-based technologies are prohibitively expensive and sluggish in the context of large amounts of data being processed due to the possibility of biased processing and a significant overhead (Motlagh et al., 2022).

CONCLUSION

The study shows conclusively that edge computing is required to support autonomous systems of smart cities in real time, reliably, and at scale. A comprehensive experimental analysis of the system with both quantitative metrics of performance and qualitative analysis of the system reveals that decentralized edge-based systems show significantly better results about the latency-sensitive and mission-critical applications compared to the traditional cloud-based systems. The performance measured indicates the significant decrease in end to end latencies values, the enhanced stability of throughputs in the presence of heavy data loads, the data transmission reduction and improvement in energy efficiency through localized processing and reduction of the packet loss in congested conditions. The results also show that the system is more robust and can better address faults as autonomous operations are still positively functioning despite the cloud connection which was lost at intervals. The decisions were further refined and quickened by the artificial intelligence of the edge of the network and allowed the self-driving cars and intelligent traffic systems to respond appropriately when the situation in the cities were shifting rapidly. The proposed equipped system can also be used to create sustainable and secure smart cities and reduce bandwidth consumption and enhance privacy through the aid of a localised data processing. This study confirms edge computing as a key technical facilitator of next-generation smart cities that offers the computational support that is required to enable more complex, data-driven, and safety-critical autonomous services. The fact that these findings not only indicate that edge computing can be deployed in the field, it also offers valuable information to city planners, system designers, and policymakers on how to develop smart, efficient, and resilient city systems.

REFERENCES

Abouaomar, A., Elallid, B. B., & Benamar, N. (2025). Optimizing energy and latency in 6G smart cities with edge cyber twins. arXiv.

Ali, M. A., & Dornaika, F. (2025). Edge artificial intelligence: A systematic review of evolution, taxonomic frameworks, and future horizons. arXiv.

Alves, H., Mahmood, N. H., López, O. L. A., Samarakoon, S., Yrjölä, S., Latva-aho, M., Juntti, M., Pouttu, A., Dekorsy, A., de Sena, A. S., Sezgin, A., Matthiesen, B., Benzaïd, C., Weeraddana, C., Hutchison, D., Marasinghe, D., Ergenç, D., Jorswieck, E., Harjula, E., … Svensson, T. (2025). 6G resilience: White paper. arXiv.

Amiroh, K., Priyambodo, T. K., & Lelono, D. (2025). A modular intelligent resource architecture: Optimizing QoS in edge–cloud fusion systems for smart agriculture. Engineering Technology & Applied Science Research, 15(5), 27696.

Bhandari, G. (2025). Edge computing for autonomous vehicles: Improving real-time data analysis and decision-making for enhanced safety and efficiency in self-driving cars. Journal of Information Systems Engineering & Management, 10, 367.

Bhattacharya, T., Peddi, A. V., Ponaganti, S., & Veeramalla, S. T. (2024). A survey on various security protocols of edge computing. Research Square.

Chebaane, A., Scholze, D., Rezgui, Y., Abdennebi, A., Al-Khatib, A., Khelil, A., Badraoui, L., & Liu, C. (2025). Fine-grained latency analysis of real-world 5G-enabled multi-tier edge computing for school zone traffic safety. Discover Internet of Things, 5(1).

Chimezie, O., Dawodu, S. O., Daraojimba, A. I., Onwusinkwue, S., Akagha, O. V., & Ahmad, I. A. I. (2024). Review of evolving cloud computing paradigms: Security, efficiency, and innovations. Computer Science & IT Research Journal, 5(2), 270.

Chinta, S. (2024). Edge AI for real-time decision making in IoT networks. International Journal of Innovative Research in Computer and Communication Engineering, 12(9), 11293.

Dardour, M., Mosbah, M., & Ahmed, T. (2024). Improving emergency response: An in-depth analysis of an ITS-G5 messaging strategy for bus blockage emergencies at level crossings. Journal of Network and Systems Management, 32(2).

Daud, A., Amo-Boateng, M., Owor, N. J., Aboah, A., & Adu-Gyamfi, Y. (2023). Edge computing-enabled road condition monitoring: System development and evaluation. arXiv.

Folorunsho, S. O., Adenekan, O. A., Ezeigweneme, C., Somadina, I. C., & Okeleke, P. A. (2024). Developing smart cities with telecommunications: Building connected and sustainable urban environments. Engineering Science & Technology Journal, 5(8), 2492–2512.

Gill, S. S., Golec, M., Hu, J., Xu, M., Du, J., Wu, H., Walia, G. K., Murugesan, S. S., Ali, B., Kumar, M., Ye, K., Verma, P., Kumar, S., Cuadrado, F., & Uhlig, S. (2024a). Edge AI: A taxonomy, systematic review, and future directions. arXiv.

Gill, S. S., Golec, M., Hu, J., Xu, M., Du, J., Wu, H., Walia, G. K., Murugesan, S. S., Ali, B., Kumar, M., Ye, K., Verma, P., Kumar, S., Cuadrado, F., & Uhlig, S. (2024b). Edge AI: A taxonomy, systematic review, and future directions. Cluster Computing, 28(1).

Guarda, T., & Torres, W. (2025). Real-time IoT with edge computing: Efficiency, security, and future trends. In Lecture Notes in Computer Science (p. 106). Springer.

Guo, L., Lin, J., Xu, X., & Li, P. (2024). Algorithmics and complexity of cost-driven task offloading with submodular optimization in edge–cloud environments. arXiv.

Ho, T. M., Tran, T. D., Nguyen, T. T., Kazmi, S. M. A., Le, L. B., Hong, C. S., & Hanzo, L. (2022). Next-generation wireless solutions for the smart factory, smart vehicles, smart grid, and smart cities. arXiv.

Iftikhar, A., Qureshi, K. N., Shiraz, M., & Albahli, S. (2023). Security, trust, and privacy risks, responses, and solutions for high-speed smart city networks: A systematic literature review. Journal of King Saud University – Computer and Information Sciences, 35(9), 101788.

Kreković, D., Krivić, P., Žarko, I. P., Kušek, M., & Le-Phuoc, D. (2024). Reducing communication overhead in the IoT–edge–cloud continuum: A survey on protocols and data reduction strategies. arXiv.

Kumar, A. (2025). AI and edge computing: Real-time collaboration in distributed systems. World Journal of Advanced Engineering Technology and Sciences, 15(1), 1037–1052.

Maciá-Lillo, A., Pujol, F. A., Jimeno-Morenilla, A., García-D'Urso, N., & Azorín-López, J. (2025). AI edge cloud service provisioning for knowledge management smart applications. Scientific Reports, 15(1).

Madake, V. (2024). Edge computing: Enhancing IoT and beyond—Implications for businesses and consumers. International Journal for Research in Applied Science and Engineering Technology, 12(12), 3077–3085.

Modupe, O. T., Otitoola, A. A., Oladapo, O. J., Abiona, O. O., Oyeniran, O. C., Adewusi, A. O., Komolafe, A. M., & Obijuru, A. (2024). Reviewing the transformational impact of edge computing on real-time data processing and analytics. Computer Science & IT Research Journal, 5(3), 693–710.

Motlagh, N. H., Lovén, L., Cao, J., Liu, X., Nurmi, P., Dustdar, S., Tarkoma, S., & Su, X. (2022). Edge computing: The computing infrastructure for the smart megacities of the future. Computer, 55(12), 54–63.

Pasupuleti, M. K. (2024). Advancing real-time intelligence with edge AI.

Pitstick, K., Novakouski, M., Lewis, G. A., & Özkaya, İ. (2024). Defining a reference architecture for edge systems in highly uncertain environments. arXiv.

Position Papers of the 18th Conference on Computer Science and Intelligence Systems. (2023). Annals of Computer Science and Information Systems, 36.

Rajagopal, S. (2025). Edge computing–smart cities: Optimizing data processing and resource management in urban environments. Journal of Information Systems Engineering & Management, 10, 473–489.

Ren, X., Vashisht, S., Aujla, G. S., & Zhang, P. (2021). Drone–edge coalesce for energy-aware and sustainable service delivery for smart city applications. Sustainable Cities and Society, 77, 103505.

Shahra, E. Q., Wu, W., Basurra, S., & Aneiba, A. (2024). Intelligent edge–cloud framework for water quality monitoring in water distribution systems. Water, 16(2), 196.

Singh, P., Kaur, A., Batth, R. S., Aujla, G. S., & Masud, M. (2021). Service versus protection: A Bayesian learning approach for trust provisioning in edge-of-things environments. IEEE Internet of Things Journal, 9(22), 22061–22074.

Xie, J., Zhou, X., & Cheng, L. (2024). Edge computing for real-time decision making in autonomous driving: Challenges, solutions, and future trends. International Journal of Advanced Computer Science and Applications, 15(7).

Zhu, M., Liang, M., Li, H., Lu, Y., & Pang, M. (2023). Intelligent acceptance systems for distribution automation terminals: An overview of edge computing technologies and applications. Journal of Cloud Computing: Advances, Systems and Applications, 12(1).

Τρίγκα, Μ., & Δρίτσας, Η. (2025). Edge and cloud computing in smart cities. Future Internet, 17(3), 118.