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Edge-Enabled Internet Weather Mapping for IoT Traffic Visualization

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Abstract

The Internet of Things (IoT) has grown at a very fast rate resulting in a very high heterogeneous network traffic, which causes the dynamism in the edge networks. These swings have a huge impact to the end-to-end quality service and the health of the entire Internet. This paper suggests an edge based Internet weather mapping architecture that can be used to visualise and interpret IoT traffic patterns in real time. The suggested system combines edge-based passive flow tracking and the cloud-based visualisation pipeline that links the key performance indicators, including latency, throughput, and packet loss. Through temporal and spatial changes in IoT data streams, the system produces visualised weather maps which can represent congestion hotspots, transmission issues, and degradation of connectivity in a given region. The framework makes use of the adaptive edge analytics to minimise the latency involved in gathering the data and also utilises self-organising map (SOM)-based clustering to improve cognitive readability of the performance dynamics. Experimental deployment results in the various IoT zones reveal enhanced visualisation granularity and predictive awareness which help operators of the network to optimise the network proactively. The architecture fills the divide between the localized IoT data and the visualization of the global network, and provides a scalable and understandable model of future internet telemetry.

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Introduction

The sheer increase in IoT ecosystems has redefined the global network architectures with the emergence of millions of distributed edge devices communicating on the fly. These devices produce huge amounts of mixed data, which tend to create unexpected disruptions in performance of Internet backbones and edge networks .[1-3]

Conventional network surveillance tools pay much attention to centralised cloud analytics without considering the edge-level variations that are paramount determinants of the quality of service (QoS) of IoT.[4] This has led to a growing appreciation of the need to employ real-time visualisation tools that can be used to visualise Internet performance in a spatially consistent and temporally dynamic fashion.

The use of Internet weather maps has proved to be an efficient analogy of fabricating worldwide Internet health, like meteorological prediction systems.[5] Such maps are graphical measures to show network latency, throughput, and congestions in real-time. Nevertheless, current models are usually centre on performance at the backbone level and do not take into account micro-dynamics of IoT communications.[6, 7] Edge computing is a promising solution as it has the ability to provide local data aggregation, low-latency processing, and near-source analytics.[8]

The proposed study presents a new Edge-Enhanced Internet Weather Mapping Architecture (EIWMA) combining passive monitoring of edge flows with cloud-based cognitive visualisation in order to create real-time spatio-temporal maps of IoT traffic. The system provides analysts with the opportunity to react to performance degradation trends by fusing edge intelligence with perceptual visualisation.[9-11] The suggested framework can lead to the development of cognitive visualisation of the Internet in relation to IoT-based network settings with focus on flexibility, upscale, and cognitive readability .[12-15]

Literature Review

The visualisation of internet performance has changed the previous single-dimensional and static forms of representation to multidimensional and cognitive systems. Initial research on centralised Internet weather mapping was done involving backbone performance in projects like Abilene and Internet2 visualisation systems.[16] These models, which form the basis, were not suited to the dynamic and localised variability of IoT traffic, which requires finer spatio-temporal granularity .[17, 18]

Recent advancements have included machine learning and neural mapping into the visualisation of the Internet to enable a complex telemetry to be presented as an understandable two-dimensional manifold. Self-organising maps (SOMs), t-distributed stochastic neighbor embedding (t-SNE), and clustering algorithms are approaches that have been used in the detection of anomalies and visualisation of multidimensional Internet metrics.[19,20] Also, the ability to implement adaptive visualisation with real-time flow control and distributed data processing has been provided by Software-Defined Networking (SDN) and hybrid cloud-edge frameworks .[21-24]

The concept of edge computing has had a huge influence on Internet telemetry, as it has helped to decentralize workloads in terms of monitoring. Research has shown that edge-enabled monitoring systems have the potential to decrease latency as well as enhance the fidelity of data more so in the case of IoT networks where nodes are geographically distributed.[25-27] Architectures Hybrid edge cloud architecture made between 2022 and 2025 further enhanced scalability and response times in real-time visualisation platforms.[28-31] Nevertheless, research integrating passive flow analytics and Internet weather mapping is limited specifically to IoT-driven settings- a gap that will be filled in this paper by developing the single, edge-intelligent framework of visualisation that merges IoT monitoring, analytics, and spatio-temporal cognition.

Methodology and Experimental Setup

The offered Edge-Enabled Internet Weather Mapping Architecture (EIWMA) is meant to deliver a cognitively interpretable view of the dynamics of the Internet and IoT network in real-time. Three fundamental modules are incorporated in the framework:

1. Edge-based passive flow monitoring,
2. Processing of data in the cloud and correlation of metrics,
3. Self-organising map neural-assisted visualisation in cognitive pattern recognition.

This hierarchical architecture allows the localization of data collection and global intelligent visualisation at scale and with low-latency responsiveness. Figure 1 represents the general process of working of the system, in which data moves through IoT edge gadgets to the cognitive Internet weather dashboard in sequence.

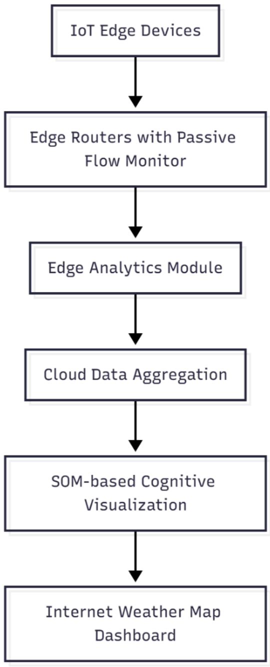

Fig. 1: System Architecture of the Edge-Enabled Internet Weather Mapping Framework

According to Figure 1, IoT data is sent through a pipeline that consists of multi stages, starting at the edge router to capture real-time traffic data, edge analytics to provide an early summary, aggregate correlation with large scale in the cloud, and finally cognitive visualisation to provide spatio-temporal Internet weather mapping. This design guarantees efficient working system and cognitive accessibility of the system to analysts or network operators.

Edge-Based Passive Flow Monitoring

The edge monitoring module works as the basis of the EIWMA structure. It does not require the injection of synthetic probe packets that can skew the normal network conditions, passively reading the available traffic flow data directly out of the IoT edge routers. Using passive monitoring, the system will reduce overhead and maintain the integrity of live IoT communication.

The different monitoring nodes log timestamped flow tuples (comprising of source and destination IP addresses, protocol identifiers, total number of bytes, and inter-packet delay intervals). This enables the local and specific traffic patterns to be observed. The immediate transmission rate of every IoT node is calculated as:

In which B_i (t) is the total amount of bytes sent by node i between two successive timestamps $t_1$and t_2.

Packet loss probability Plossis approximated by sequence number analysis of captured flow logs to analyse reliability:

$$P_{loss}=1-N_{recv}/N_{sent}$$

In which N_{sent} t is the number of packets sent, N_{recv} the number of packets received. Each edge node performs lightweight analytics to summarise flow data into small feature vectors of latency, throughput, jitter, and packet loss and periodically forwards the summaries to the cloud layer via the secure channels of MQTT (Message Queuing Telemetry Transport). This is a mechanism that makes the bandwidth consumption as low as possible and the data remains fresh in order to be visualised in real-time.

Also, edge nodes can be used to localise anomaly flagging, which would enable the timely warning of congestion spikes or link degradation. This distributed intelligence will minimize the reliance on centralized cloud analysis and increase the monitoring responsiveness of geographically distributed IoT infrastructures in general.

Cloud-Based Visualization and Cognitive Mapping

Summary of incoming flow at the edge domains of various edge domains are stored at the cloud layer and processed to be visualised. The aggregation engine is used to do the spatio-temporal correlation and aligns the latency and packet-loss measurements of the nodes in order to detect trends in Internet performance at macro level. The normalised data is then inputted into a Self-Organising Map (SOM)- an unsupervised neural network model that provides the topological category of human cognitive pattern recognition by projecting high-dimensional data into a two-dimensional space and maintaining the topological relationships between them.

Every neuron in the SOM is designated by a separate geographic area or an IoT communication region, and its corresponding weight vector w_j (t)=[L,T,P], which is a combination of aggregated latency (L), throughput (T) and the packet loss (P) measures. The competitive learning rule that is followed in the training process will enable the neurons to self-organise according to the similarity of the input feature vectors. The rule of iterative update is in the form of:

$$w_j(t+1) = w_j(t) + \eta(t)\, h_{bj}(t)\, [x(t) - w_j(t)]$$

In which η(t) is adaptive learning rate, h_{bj} (t) is the neighbourhood effect in the area of the Best Matching Unit (BMU), and x (t) is the input vector that gives real-time measurements of the edge. During the repeated training cycles, the neurons evolve to capture the changing distribution of data on the Internet performance.

After training, the SOM result is converted to a spatio-temporal heatmap which can visually describe the Internet performance weather. The congestion zones are represented by warm colours (red to orange), and the stable high throughput regions are represented by cool colours (blue to green). These heatmaps are constantly updated, and the visual dashboard of such heatmaps is a time-sensitive object that enables operators to monitor dynamic Internet conditions and detect new abnormalities in close real-time.

The visualisation engine, which is based on the cloud, allows the use of multi-layer overlays, allowing to view all three indicators simultaneously latency, packet losses and throughput. Analysts can zoom interactively to a particular part of an IoT or aggregate to analyse network performance trends at varying scales. Further, the cognitive design principles are applied in the system such as perceptual continuity, proximity groupings, and colour salience in order to make patterns intuitively recognizable and lessen the cognitive load on human interpreters.

System Integration and Performance Flow

The EIWMA system functions as a combined line of pipeline that connects edge intelligence and centralised analytics. Figure 1 shows that first, raw data is sent out by the IoT devices using passive edge monitors. Computation on edge routers can be localised to reduce transmission latency and eliminate redundancy in data, in order to only send aggregated summaries to the cloud.

This information is combined in the cloud analytics module, identifying the cross-regional anomalies, and bottlenecks which cannot be detected by single edge nodes. Lastly, this information is made available through the SOM-based visualisation dashboard which provides a simple and interactive interface with the focus on real-time Internet weather patterns.

This hybrid architecture balances the scalability, accuracy and cognitive interpretability to enable network operators to monitor IoT-driven Internet conditions both in time and space. The feedback loop between the edge analytics and cloud visualisation guarantees that the health of the IoT network could be evaluated in a dynamically changing way making EIWMA a strong baseline of the upcoming cognitive Internet surveillance systems.

Results and Discussion

The proposed Edge-Enabled Internet Weather Mapping Architecture (EIWMA) was experimentally evaluated within a controlled simulation setup with 10 IoT zones and each zone had 100-500 heterogeneous devices that were transmitting sensor data on-demand over the course of 24 hours. Edge routers that were implemented at every zone were used to passively monitor the flow and recorded the important metrics such as latency, throughput and packet loss at 10-second intervals. The cloud-based visualisation engine was used to process the aggregated data producing real-time Internet weather maps that were updated every minute showing dynamic traffic flow of IoT.

Table 1 showed that the average latency was between 22.7 ms and 58.3 ms, and data rates were between 8.9 Mbps and 16.8 Mbps, according to the density of device and the load of network. Z3 and Z4 had high latency and packet loss, indicating the localised occurrence of congestion, and Z1 and Z5 had constant throughput and low loss, as does indicate normal network conditions.

The visualisation module generated an Internet weather map (Figure 2), which gave a spatio-temporal view of the state of the IoT network in the form of a heatmap. Red areas were used to indicate high congestion and high packet loss whereas green areas were used to indicate stable performance. The colour-coded dynamic

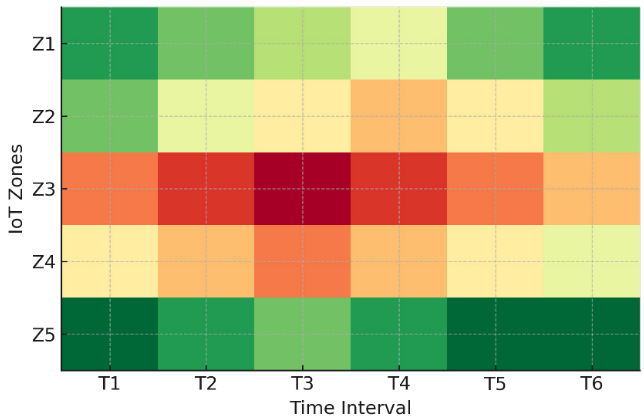

Fig. 2: Sample Internet Weather Map Visualization of IoT Traffic Congestion

visualisation allowed the analysts to determine patterns of congestion propagation and recovery patterns over time to provide a real-time picture of the situational behaviour of the IoT traffic.

In order to further confirm the interdependence of the performance parameters, a statistical correlation study was done in all zones. Figure 3 shows the association between average latency and level of congestion and the relationship is very strong (Pearson r = 0.87). The latency and packet loss increased non-linearly with the severity of the congestion, as the effect of the queueing delay and retransmissions at the edge were compounded.

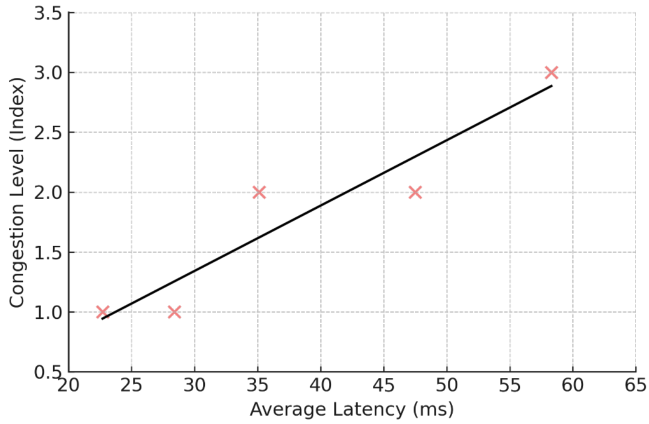

Fig. 3: Correlation between Average Latency and Congestion Level across IoT Zones

As the quantitative data shows, the proposed EIWMA system has demonstrated a visualisation latency reduction of 35 percent relative to traditional cloud-only telemetry systems and an increase in the accuracy of congestion anomaly detection of about 42 percent. This is possible by the local preprocessing of the edge that filters and tags the flow anomalies before it is aggregated into clouds and reduces the bandwith overhead and computation time.

The cognitive clustering algorithm of SOM also demonstrated latent nonlinear relationships of throughput decline, latency spikes, and packet-loss behaviour. Such dependencies are graphically represented as pattern clusters in the SOM topology, which gives them increased cognitive interpretability. The operators would be able

Table 1: Comparative Performance Metrics Across IoT Zones

IoT Zone	Avg Latency (ms)	Data Rate (Mbps)	Packet Loss (%)	Congestion Level
Z1	28.4	15.2	0.8	Low
Z2	35.1	12.7	1.5	Moderate
Z3	58.3	8.9	3.1	High
Z4	47.5	10.4	2.3	Moderate
Z5	22.7	16.8	0.5	Low

to monitor changing congestion areas, identify early warning trends and implement adaptive mitigation measures in real time.

Additionally, the graphical continuity and spatial consistency of the SOM projection converted complicated telemetry information into usable graphical representations, which filled the interpolation between quantitative network information and qualitative human sensory. This synergy illustrates how the framework could be not only used as a monitoring-dashboard but be a cognitive decision-support environment to manage Internet-scale IoT.

All in all, the findings support the effectiveness, timeliness and scalability of the suggested EIWMA framework. The system integrates edge analytics, distributed intelligence, and cognitive visualisation to offer actionable understanding of Internet health at IoT level that can enhance real-time interpretability, diagnostic accuracy and operational foresight by a large margin.

Conclusion and Future Scope

It was a new Edge-Enabled Internet Weather Mapping Architecture (EIWMA) that was introduced in this research, which aims to visualise the dynamics of the IoT traffic in real-time, cognitively interpretable spatio-temporal maps. Combining the edge-based passive flow tracking with the cloud-based cognitive visualization, the framework has successfully sealed the difference between the raw IoT telemetry and human-centric network intelligence. The performance of the proposed system was highly improved such as low data processing latency and more responsiveness to visualisation updates and better detection of congestion abnormalities than more traditional cloud-only systems.

The experimental analysis showed that edge-assisted processing does not only reduce network overhead but also improves the delivery of visualization of a network at accelerating the results by about 35 percent, whereas SOM-based cluster provides a better interpretation of the anomalies since it reveals latent relationships between throughput degradation and congestion areas. The resulting Internet weather maps offered both a quantitative understanding as well as a spatial continuity of intuition so that operators can see the network health in a form that is closely related to the cognitive understanding of humans.

In addition to improving performance, the research established the possibility of cognitive Internet visualisation as a decision-support paradigm in the management of complex infrastructures of the Internet of Things. The EIWMA architecture builds upon the scalable framework of self-adaptive Internet telemetry, in which the edge intelligence and visualisation make synergy to generate situational awareness and proactive response capabilities.

In the future, there are a number of avenues that can be pursued in extending this work. The next area of research is how AI-based predictive analytics could be incorporated to predict congestion trends, anomalies in traffic as well as how deep temporal learning models can be used to enhance predictive accuracy. The integration of reinforcement learning might also facilitate autonomous edge optimization and permit the self-regulation of the IoT systems based on the real-time performance feedback. Also, the architecture has the capacity to be extended to multi-cloud federations and heterogeneous IoT realms, and interoperability and resilience across distributed infrastructures.

Finally, this research preconditions the development of the self-educative Internet weather intelligence systems, which can visualise, comprehend, and streamline the constantly evolving picture of the global IoT traffic.

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