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***Abstract*—The exponential growth of connectivity and computing demand has made Network Function Virtualization Infrastructure (NFVI) major contributors to global energy consumption. Conventional network and service deployments, whether based on legacy hardware appliances or NFVI stacks, struggle to dynamically provision resources for peak data traffic demand. This results in nearly constant energy consumption even during low-traffic periods, leading to inefficient resource use. Network softwarization and virtualization have enabled flexible and programmable service deployments, which are beneficial for rapid and dynamic scaling of network functions. This paper validates energy-aware service and network orchestration with a Zero-touch Network and Service Management (ZSM) framework for autonomous optimization of computing, network, and power resources from NFVI on a use case focused on connected mobility, and in particular, smart traffic management. By modeling road traffic based on vehicle count and type and 3rd Generation Partnership Project (3GPP) profiles for data formats in vehicular communication scenarios, the ZSM framework adjusts services and resources to services requirements and to actual demand. Experimental validation on the real-life Smart Highway testbed in Antwerp (Belgium) demonstrates a strong correlation between vehicular traffic and power consumption, supporting the hypothesis that adaptive compute and network resource management reduces unnecessary energy use and advances the vision of sustainable and self optimizing Sixth-Generation (6G) networks.**

I. Energy-Awareness Experiment 1

This is my starting point [1,2]

Every physical capability of the Roadside Unit (RSU) is different from each other in terms of maximum wattage. When the RSUs were stressed based on the amount of vehicles, they have a limit of watts also linked to the CPU consumption.

TABLE I
Average vehicular counts and power consumption per RSU.

RSU	**Night (17:00–06:00)**		**Day (06:00–17:00)**	
	Vehicles	Power (W)	Vehicles	Power (W)
1	0	59	4	58
2	1	55	7	55
3	5	56	23	56
5	2	51	7	51
6	1	60	5	60
7	6	61	16	61

Table III summarizes the maximum number of users (U) and the corresponding maximum wattage (W) capacity for each RSU. As shown, RSU 5 supports the highest number of vehicles and reaches a higher power consumption compared to the others. This variation highlights the heterogeneous nature of the RSUs in the testbed. Figure 1 visually presents the relationship between the number of vehicles and the power consumption for each

TABLE II
Location mapping between inductive sensors and RSUs to monitor vehicular traffic per RSU in the E13 Highway, Antwerp Belgium.

RSU	**Vehicles**	**RSU Location**	**Nearest Inductive Sensor**
1	12	51.210575, 4.46655	51.21056678, 4.466446158
3	25	51.215186667, 4.450568333	51.21587307, 4.452993707
7	12	51.210616667, 4.480896667	51.21066931, 4.480559376
8	26	51.211091667, 4.491425	51.21127494, 4.491424033
4	16	51.21574, 4.457151667	51.21577734, 4.457154961
6	16	51.211236667, 4.472586667	51.21121407, 4.472483657

RSU, illustrating how the power usage increases with the load and reaches a plateau at the maximum capacity.

Max vehicles registered: 39 RSU 5

TABLE III
Maximum U and W capacity for each RSU.

RSU	Max U	Max W Capacity
1	27	69
2	27	67
3	27	70
5	36	68
6	27	77
7	31	75

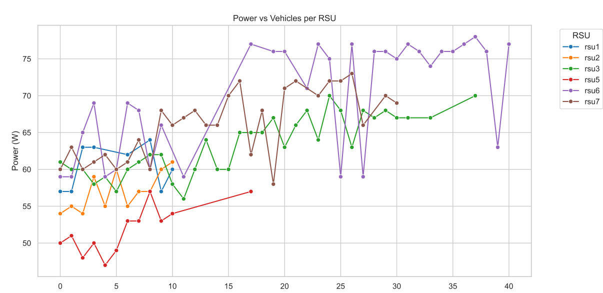

Fig. 1. Relationship between the number of vehicles and power consumption for each RSU, showing how power usage increases with load and plateaus at maximum capacity.

A. Data Analysis and Impact

A detailed analysis of the collected data, exported to a CSV file, provides deeper insights into the energy consumption patterns of the RSUs. The analysis involved calculating the energy efficiency, defined as vehicles per watt, and modeling the power consumption trend using linear regression for each RSU. The energy efficiency was computed by dividing the number of vehicles by the corresponding power consumption (in watts) for each data point. The trend was determined by applying a first-degree polynomial fit to the vehicle and power data for each RSU, which yields a linear model representing the expected power usage as a function of the number of vehicles.

The data confirms a strong positive correlation between the number of connected vehicles and power consumption across all RSUs. The linear trend reveals that as more vehicles connect, the power draw increases, which is expected. However, the rate of this increase varies, highlighting the differences in hardware and configuration among the units. For instance, RSU6 shows a steeper power consumption curve compared to RSU5, indicating it consumes more power for each additional vehicle.

The impact of these findings is significant for network management:

- **Energy-Aware Load Balancing:** By understanding the unique power profile and efficiency of each RSU, a central orchestrator can make smarter, energy-aware decisions. For example, during periods of low network traffic, vehicles can be consolidated onto the most energy-efficient RSUs, allowing others to be put into a low-power state.
- **Predictive Resource Management:** The trend models allow for the prediction of power consumption based on anticipated traffic loads. This enables proactive resource allocation and helps prevent over-provisioning, thereby reducing operational costs and the carbon footprint of the infrastructure.
- **Heterogeneity as an Advantage:** The inherent heterogeneity of the RSUs can be leveraged as an advantage. High-demand, performance-critical applications can be assigned to the most powerful RSUs, while less demanding tasks can be handled by more energy-efficient, lower-capacity units, optimizing the overall performance and energy usage of the system.

To illustrate the calculations, consider a data point for RSU1 where it serves 6 vehicles and consumes 62.0 watts. The energy efficiency is calculated as:

$$\text{Vehicles per Watt} = \frac{6 \text{ vehicles}}{62.0 \text{ W}} \approx 0.097$$

This metric indicates how many vehicles are being served for each watt of power consumed. For the trend analysis, a linear model of the form $P(v) = m \cdot v + c$ is fitted to the data for each RSU, where P is the power, v is the number of vehicles, m is the slope (power increase per vehicle), and c is the y-intercept (base power consumption). For RSU1, the model might yield a trend value of approximately 60.53 W at 6 vehicles, representing the expected power consumption based on the overall behavior of that specific unit. This allows for a standardized comparison of expected versus actual power draw.

II. TODO'S

1) The evaluation shows qualitative correlations and an illustrative table/figure, but lacks clear quantitative metrics (e.g., % energy saved, baseline comparison, statistical significance, confidence intervals).
2) The MCDM method and parameter choices (weights, thresholds, ranking rules, how priority between latency vs energy is negotiated) are not fully specified and appear ad-hoc. This hurts reproducibility and clarity.
3) The paper lacks discussion/measurements of orchestration latency, control-plane overhead, the time to migrate/scale services, and the energy/CPU cost of running the ZSM analytics itself.
4) Validation focuses on a "best-effort infotainment" profile; safety-critical or low-latency V2X services (the most energy-sensitive/critical) are not evaluated.
5) No error bars or statistical tests are shown; it is unclear how repeatable the experiments are and whether observed effects are significant.
6) If possible, emulate denser scenarios (more RSUs or higher vehicle densities) or use simulations to show how the approach scales beyond the eight-RSU testbed. Discuss limitations for urban scenarios.

***Abstract*—Intelligence in Zero-touch Service Management (ZSM) is pivotal for achieving fully autonomous network and service operations. By embedding advanced artificial intelligence (AI) and machine learning (ML) techniques within the ZSM framework, networks can proactively monitor, analyze, and optimize their own performance with minimal human intervention. This enables dynamic adaptation to changing network conditions, efficient resource allocation, and rapid fault detection and resolution. In the context of ZSM, intelligence facilitates closed-loop automation, allowing the system to learn from operational data, predict future states, and make informed decisions to enhance service quality and reliability. As networks evolve towards 6G and beyond, the integration of intelligence in ZSM is essential for supporting complex, heterogeneous environments and delivering on the promise of self-optimizing, resilient, and sustainable network infrastructures.**

III. Intelligence Experiment 1

This section presents the first experiment conducted to evaluate the role of intelligence in network automation. The experiment focuses on the integration of artificial intelligence (AI) and machine learning (ML) functions within the Zero-touch Service Management (ZSM) framework. The objective is to assess how these technologies contribute to optimizing network operations and enabling autonomous decision-making processes [3].

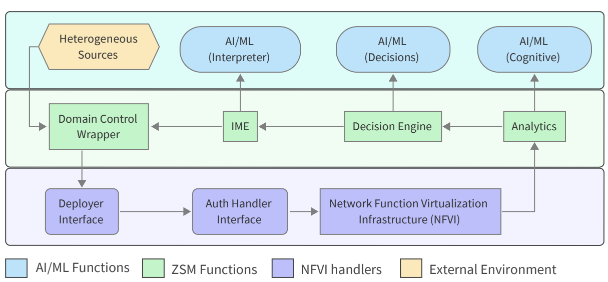

Fig. 2. AI and ML functions within the ZSM framework, illustrating their role in enhancing network automation and optimization.

***Abstract*—Network resiliency is essential for ensuring continuous and reliable service delivery in the face of failures, attacks, or unexpected events. As networks become more complex and critical to daily operations, designing resilient architectures and mechanisms is paramount. This topic explores strategies and technologies that enhance network robustness, including redundancy, fault tolerance, rapid recovery, and adaptive reconfiguration. Emphasis is placed on proactive monitoring, automated response, and the integration of intelligent systems to detect and mitigate disruptions. By advancing network resiliency, organizations can minimize downtime, maintain service quality, and support the evolving demands of modern digital infrastructures.**

IV. Resiliency Experiment 1

This section presents the first experiment conducted to evaluate the role of resiliency in network automation. The experiment focuses on the integration of advanced fault tolerance and rapid recovery mechanisms within the Zero-touch Service Management (ZSM) framework. The objective is to assess how these technologies contribute to optimizing network operations and enabling autonomous decision-making processes [3].

ACKNOWLEDGMENTS

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