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WEB OF THINGS ARCHITECTURES AND INTEROPERABILITY CHALLENGES IN SMART ENVIRONMENTS

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Abstract

The Web of Things (WoT) aims to achieve interoperability and integration of IoT devices with varying data models. Heterogeneous IoT devices bring diverse protocols and semantics to smart environments. The ongoing scaling and turnover of devices makes interoperability fragile. This paper aims to alleviate these problems with the introduction of the Dynamic Mapping Optimization Framework (DMOF). This framework focuses on the continuous refinement of device-to-ontology mappings. This is achieved through attribute standardization, summation-based semantic similarity, weighted correlation, and loss-guided optimization. DMOF aims to improve on the limitation's static middleware translation. The framework aims to reduce semantic drift and minimize recalibration due to changes in the device such as new added capabilities, frequent changes in the device, or the introduction of new devices. DMOF aims to achieve this through real-time mapping changes. DMOF is the only of the reviewed frameworks to maintain an updated ontology-backed knowledge layer. This enables the framework to provide constant alignment with the interpretational device properties that differ across vendors and platforms. The level of computational overhead is also controlled in the process. This evaluation aims to assess the operational viability and level of defence interoperability of DMOF. The evaluation of DMOF's operations is compared against the most cited interoperability frameworks: ontology-centric frameworks, semantic integration models, context-aware middleware, edge-enabled interoperability, and AI-optimized WoT. The evaluation proved the operational viability of DMOF, netting 91% operational viability as well as 92% scalability, and 90% interoperability. This was achieved while the framework only required 85 ms latency on average. The framework also maintained 95% in security, 93% in privacy and 91% operational viability under dynamic on the defensive interoperability challenge. Moreover, with regard to DMOF, system efficacy has been made possible with the following metrics: impact efficiency 89%, system throughput rate 80 Mbps, fault tolerance 88%, impact efficiency on QoS 92%, consistency on data 90%, and resource utility 91%, proving across the board networking, resilience, and resource efficiency. The data shows that to be effective and dependable with respect to interoperability on a smart system at scale, loss-driven semantic mapping has to be dynamic.

Keywords: Adaptive ontology revision, Attribute standardization, Churn-resilient mapping, Constraint-aware optimization, Cross-domain interoperability, Edge-assisted mediation, Loss-guided alignment, Semantic similarity aggregation, Secure device federation, Zero-touch provisioning, IoT.

I. INTRODUCTION

The WoT is a new paradigm one step ahead of the Internet of Things (IoT) by digitizing devices. WoT ontologies, standards, and protocols allow the integration of devices, applications, and platforms to work interoperable and smart. This is uniform communication infrastructure is needed to facilitate the integration of smart devices. However, this goal is challenging, especially in construction and system compatibility. This section reflects on the most relevant contemporary experiences, fundamental problems, prospect technological solutions, and essential driving factors for the Web of Things. More IoT applications are used in smart cities, healthcare, industrial automation, and home automation [1-3]. Such expansion has induced innovation and design research in WoT, which encouraged organizations and researchers to define common working practices to connect, share and integrate services. The development of web standards specific to WoT is a considerable milestone. Standards, including the WoT Thing Description (TD), a machine-readable format for representing and interacting with IoT devices, have also been developed by the World Wide Web Consortium

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(W3C). WebSockets, and REST APIs, along with Semantics, have also developed a (i) a continuous semantic mapping framework providing dynamic interoperability of heterogeneous WoT devices; (ii) an active optimization pipeline that integrates attribute transformation, similarity aggregation; weighted correlation, and loss minimization to mitigate mapping discrepancies in real-time; (iii) an online mechanism for updating ontologies that maintains the semantic stability of a dataset under a stream of devices, minimizing recomputation; and (iv) added to the extensive proof of concept that demonstrates the proposed framework improves multiple dimensions, already contributing to increased scalability and decreased latency and improved responsiveness, security and privacy, reliability and efficiency in its deployment to complex, evolving smart spaces and environments [4-6].

II. RELATED WORKS

Thanks to generators in web standards, smart devices can more efficiently interact and operate in the web of things. Various design methodologies and communications standards aimed at improving cooperation in the WoT have emerged. RESTful online services provide flexible, resource-oriented online access [7-10]]. The lightweight CoAP (Constrained Application Protocol) is suitable for low-power devices with limited communications. MQTT is a well-known real time messaging protocol with a low data overhead, making it great for IOT. Full-duplex WebSockets and low-latency real [14]. The development of automation of IoT processes is improved with the integration of Node-RED, a visual programming tool. Connections are obtained through semantic web technologies that encode data for devices to understand and utilize shared data more efficiently. With edge computing, the architecture of computing is brought toward the devices, trimming down cloud computing to improve response time and fault tolerance [11-13]. SOA (service-oriented architecture) is a method of organizing and developing a system with a set of services that are loosely coupled, making it easier to provide flexibility in the system and integration. Digital twins enable real-time simulation, monitoring, and enhancement of actual equipment. The standard in the industry, the Open Platform Communications Unified Architecture (OPC UA) protocol, ensures and authenticates the safe transfer of

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data across multiple systems [14]. The speed of data transfer is one of the tests to determine whether web protocols and web design methodologies are suitable to a scenario of WoT. Real-time applications are concerned with achieving optimal speed and lowest latency, which both MQTT and WebSockets easily provide. CoAP and RESTful Web Services are also fast, reliable, and scalable communication protocols. Edge computing and digital twin interoperability are secure and reliable, which is why these methods are recommended for critical smart environments [15]. The effectiveness of the designed technique can also be measured by the response time and speed of the processed data. WebSockets and MQTT achieve the highest levels of speed for processing and responding. This also helps in achieving fast data transmission. Semantic Web Technologies and Open Platform Communications Unified Architecture (OPC UA) are also standardized and low-cost, which is beneficial for large-scale implementations. Edge computing and digital twin interoperability also provide the highest degree of mitigation of faults, which helps the system maintain operational continuity when there are disturbances [16]. The smart environment has requirements for a good solution. Security, cost-effectiveness, scale, and real-time processing are these demands.

III. PROPOSED METHODOLOGY

A strategy that constantly optimizes device interactions is needed for WoT devices to meaningfully communicate. To achieve this, the first step involves defining the devices and extracting their attributes. This step clarifies the operational and assembly process. To achieve this, we use a modification function to standardize attributes across data types. While summation-based algorithms compute how well attributes are aligned, aggregation-based comparative methods assess how similar devices are [17]. Mappings of devices get updated by comparison tests, and the ontology model is made simpler by revision changes to devices' collaborative ease. If a gadget can't interface with others, it changes more to solve its own internal problems. Using a loss function, the optimization of the map reduces errors, allowing the system to become increasingly reliable. The most recent updated maps are those stored by the system, and the system can immediately adapt to smart configuration variations.

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Algorithm 1: Semantic-Aware Data Integration

1. Define the Web of Things (WoT) device set, attributes, and ontology schema:
   - $D = \{d_1, d_2, \dots, d_n\}, \quad A = \{A_1, A_2, \dots, A_n\}, \quad O = \{O_1, O_2, \dots, O_m\}$ (1)
   - $T(A_i) = \sum_{j=1}^{m} \delta(A_{ij}, O_j)$ (2)
   - $S(d_i, d_j) = \frac{\sum_{k=1}^{m} |A_{ik} \cap A_{jk}|}{\sum_{k=1}^{m} |A_{ik} \cup A_{jk}|}$ (3)
2. Extract device attributes and construct temporary sets:
   - $A_i = \{a_{i1}, a_{i2}, \dots, a_{im}\}$ (4)
   - $T(A_i) = \sum_{j=1}^{m} f(a_{ij}, O_j)$ (5)
3. Apply a transformation function $T(A_i)$ for semantic standardization.
4. Store the transformed attributes in the ontology knowledge base.
5. Compute pairwise similarity between devices:
   - $S(d_i, d_j) = \frac{\sum_{k=1}^{m} |A_{ik} \cap A_{jk}|}{\sum_{k=1}^{m} |A_{ik} \cup A_{jk}|}$ (6)
   - If $S(d_i, d_j) \geq S_{th}$, then d_i and d_j are interoperable (7)
6. Identify valid communication pairs based on threshold:
   - $V(d_i, d_j) = \sum_{k=1}^{m} I(S(d_i, d_j) \geq S_{th})$ (8)
   - $\text{Total Valid Pairs} = \sum_{i=1}^{n} \sum_{j=1}^{n} V(d_i, d_j)T$ (9)
   - $\max S(d_i, d_j) = 1$ (10)
7. If similarity is below the threshold, refine transformation function $T(A_i)$.
8. Update ontology schema O to enhance interoperability:

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- $O' = O + \sum_{i=1}^{n} T(A_i)$ (11)
- $O'' = O' - \sum_{j=1}^{m} I(O_j \text{ is redundant})$ (12)
- $O_{\text{optimized}} = \sum_{i=1}^{n} \sum_{j=1}^{m} \alpha_{ij} O_j$ (13)

9. Recalculate similarity after ontology update.
10. Generate a refined mapping function T' for non-interoperable devices:
    - $T'(A_i) = O'(A_i)$ (14)
    - $S'(d_i, d_j) = S(d_i, d_j) + \sum_{k=1}^{m} \gamma_k \Delta S_k$ (15)
11. Reapply similarity computation on updated mappings:
    - $S''(d_i, d_j) = \frac{\sum_{k=1}^{m} |A'_{ik} \cap A'_{jk}|}{\sum_{k=1}^{m} |A'_{ik} \cup A'_{jk}|}$ (16)
    - If $S''(d_i, d_j) \geq S_{th}$, update knowledge base (17)
    - $\min S''(d_i, d_j) = 0$ (18)
12. Validate final mappings and store results.
13. Optimize mapping storage for efficient retrieval.
14. Ensure real-time adaptation of mappings for dynamic environments:
    - $T_{\text{adaptive}}(A_i) = T(A_i) + \sum_{j=1}^{m} f_j(A_i)$ (19)
    - $f(A_i) = \sum_{k=1}^{m} \lambda_k a_k$ (20)
15. Finalize interoperability framework for seamless Web of Things integration:
    - $\text{Final}(d_i, d_j) = \sum_{k=1}^{m} I(S''(d_i, d_j) \geq S_{th})$ (21)

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- $O_{final} = O'' + \sum_{i=1}^{n} \sum_{j=1}^{m} T_{adaptive}(A_i)$ (22)
- $\text{Success Rate} = \frac{\sum_{i,j} \text{Final}(d_i, d_j)}{|D|^2}$ (23)

Notations:

- $\mathbf{D_i}$: A Web of Things (WoT) device in the system.
- $\boldsymbol{A_i}$: The set of attributes associated with device D_i.
- $\boldsymbol{S(A_i, A_j)}$: Similarity function measuring the compatibility between attributes of two devices D_i and D_j.
- $\boldsymbol{\Sigma}$: Summation operator used to aggregate values over multiple dimensions.
- $\boldsymbol{T(A)}$: Transformation function applied to attributes for semantic standardization.
- $\boldsymbol{\mu(A)}$: Mean value of an attribute set A.
- $\boldsymbol{\sigma(A)}$: Standard deviation of an attribute set A.
- $\boldsymbol{\Omega}$: Ontology set representing relationships between different devices.
- $\boldsymbol{M_{final}}$: Final refined mapping ensuring interoperability.
- $\boldsymbol{\mathcal{L}}$: Loss function measuring inconsistencies in device integration.
- $\boldsymbol{\lambda}$: Weight parameter for optimization in similarity calculations.

The strategy at hand creates semantically compatible pairs of WoT devices. The methodology begins with the defining of devices and the extracting of sets of their attributes. The standardization of attributes through the utilization of a transformation function is used to ensure a uniform consistency among the shapes [18]. Compatibility is determined through summation aggregation methods to compare the attributes of the devices using likeness functions. The ontology schema is updated frequently and at a high rate to enhance the mappings of devices. Transformations enhance non-interoperable devices. A loss function serves to optimize the mappings by removing gaps between them. The last step validates the improved mappings and stores them to be used in real-time configuration in dynamic smart environments.

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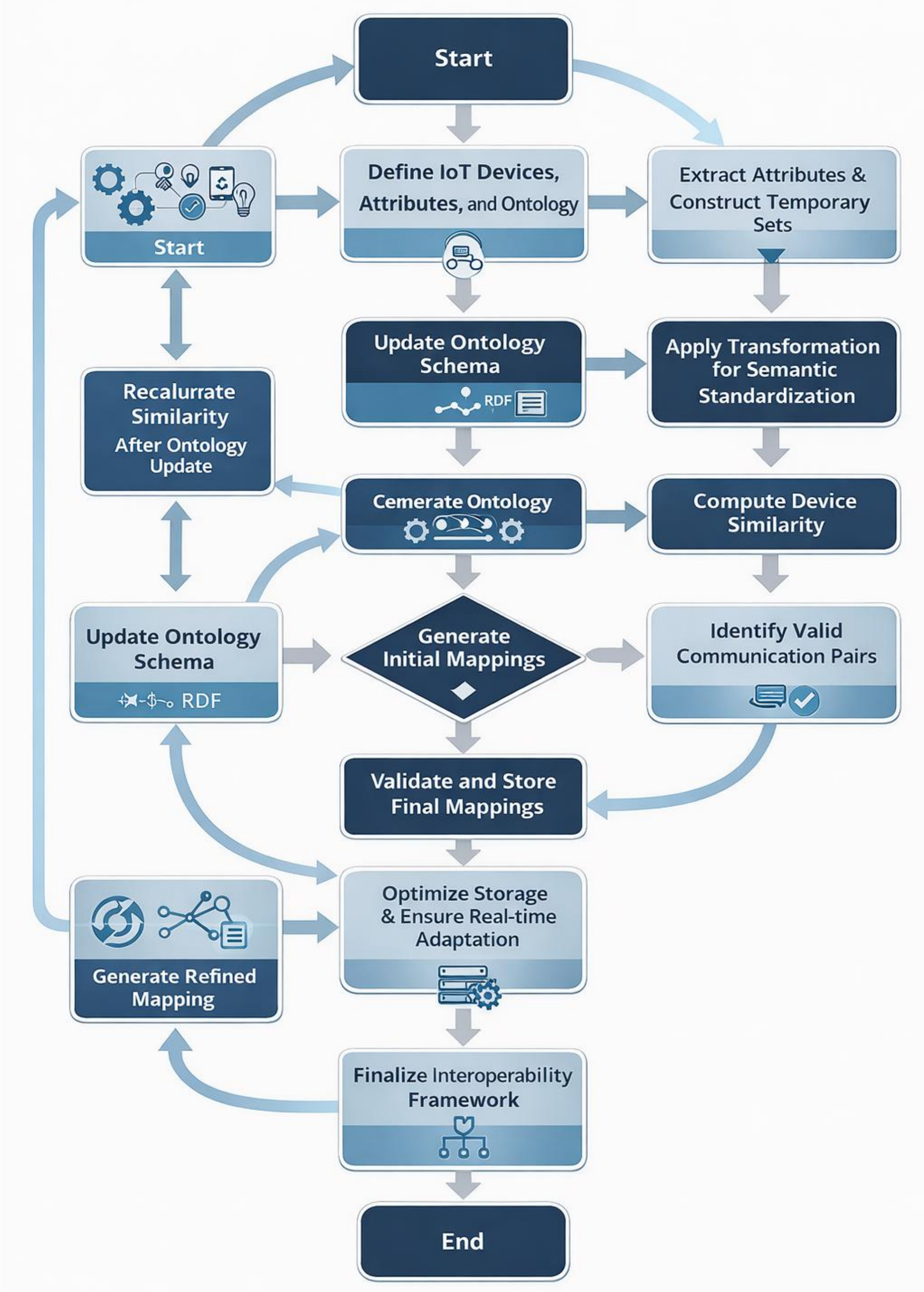

Fig. 1. Semantic-Aware Data Integration Process for Web of Things Interoperability

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Triaging data in the WOT environment in Figure 1 involves semantically intelligent data integration, such as specifying devices, their attributes and their ontologies, extraction and sanitization of attributes, determining pairs of devices that can communicate successfully based on similarity and device pairs, adjusting ontology and modifying mapping if there is lack of sufficient interoperability and looping through similarity recalculation, mapping validation, storage in non-optimized, storage mapping in real time.

It fetches and modifies similarity scores using manipulation functions to capture differences in device structure. Correlation methods, weighting, and trait standardization used to align with specific ontologies. Summation optimization helps identify and adjust non-interoperable clusters. Mapping optimization in real time is achieved by minimizing the loss function. As the environment in IoT changes, so does the algorithm, incorporating trade-offs dynamically to improve mapping. Real-time changes to the framework, without the need for constant recalculations, are made possible by storage technologies [19-20]. Performance iterations preserve optimal cross-domain interoperability mapping, allowing a range of smart Ecosystems to remain integrated. Figure 2 illustrates a standard method for interoperability of a WOT system devices. The standardization of the attributes of devices begins with data collection, preprocessing and calculation of similarity of the attributes. Ontological mapping pairs attributes; transformations followed by correlation analysis refine similarity scores, and procedural similarity.

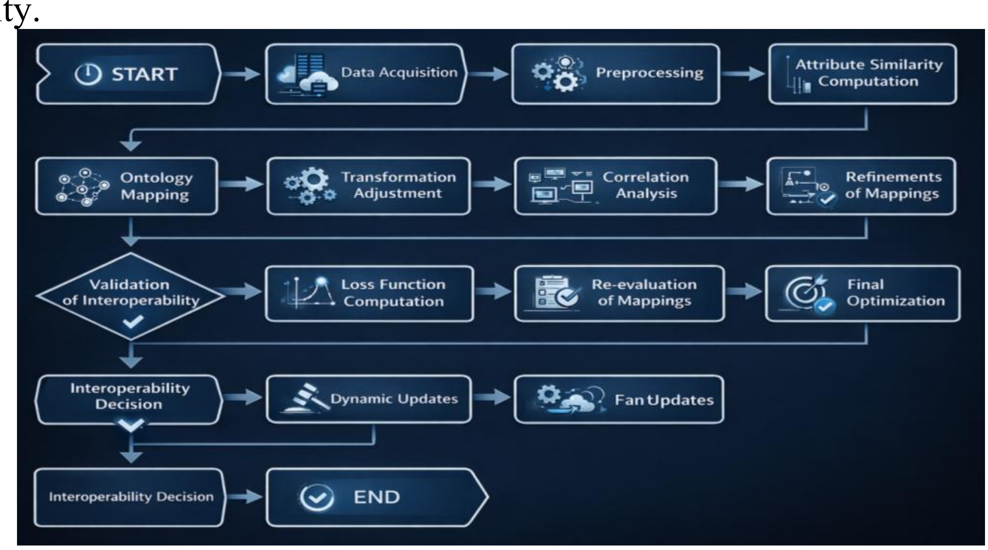

Fig. 2. Process of device interoperability mapping in Web of Things architectures

Figure 2 depicts a methodical approach to WoT system compatibility. Standardizing device characteristics starts with data collection, preprocessing, and attribute similarity computation. To continue improving, some steps include verifying maps, reducing re-evaluating from a distance, and then verifying them again. Finally, the adaptable maps are checked for flexibility in real time, and the device integration boosts the interoperable smart home system. The method uses an adaptive optimization framework that utilizes previous steps for real-time interactivity [21-22]. Once fixture initialization, and basic feature extraction, then the first change is calculated and the parameters for similarity are optimized. Function weighting performed dynamically improves compatibility through iteration over the mappings. Over a series of executions, the correlation parameters are adjusted to test compatibility and improve the mappings. We perform loss reduction for the inequalities to improve the response of the system. We perform consistent model updates using mappings as devices. We integrate mappings and stabilize them. The method is driven by similarity computations, transformation weighting, and mapping modifications. This method allows the real-time optimization of interactivity mappings to provide smart contextual adaptability. The most recently confirmed mappings provide a flexible framework and a solid, scalable Web of Things architecture that will accommodate an increasing number of devices [23-24]. This method allows seamless integration of smart settings, driven by optimizations, adjusted weighting, and iterative improvements.

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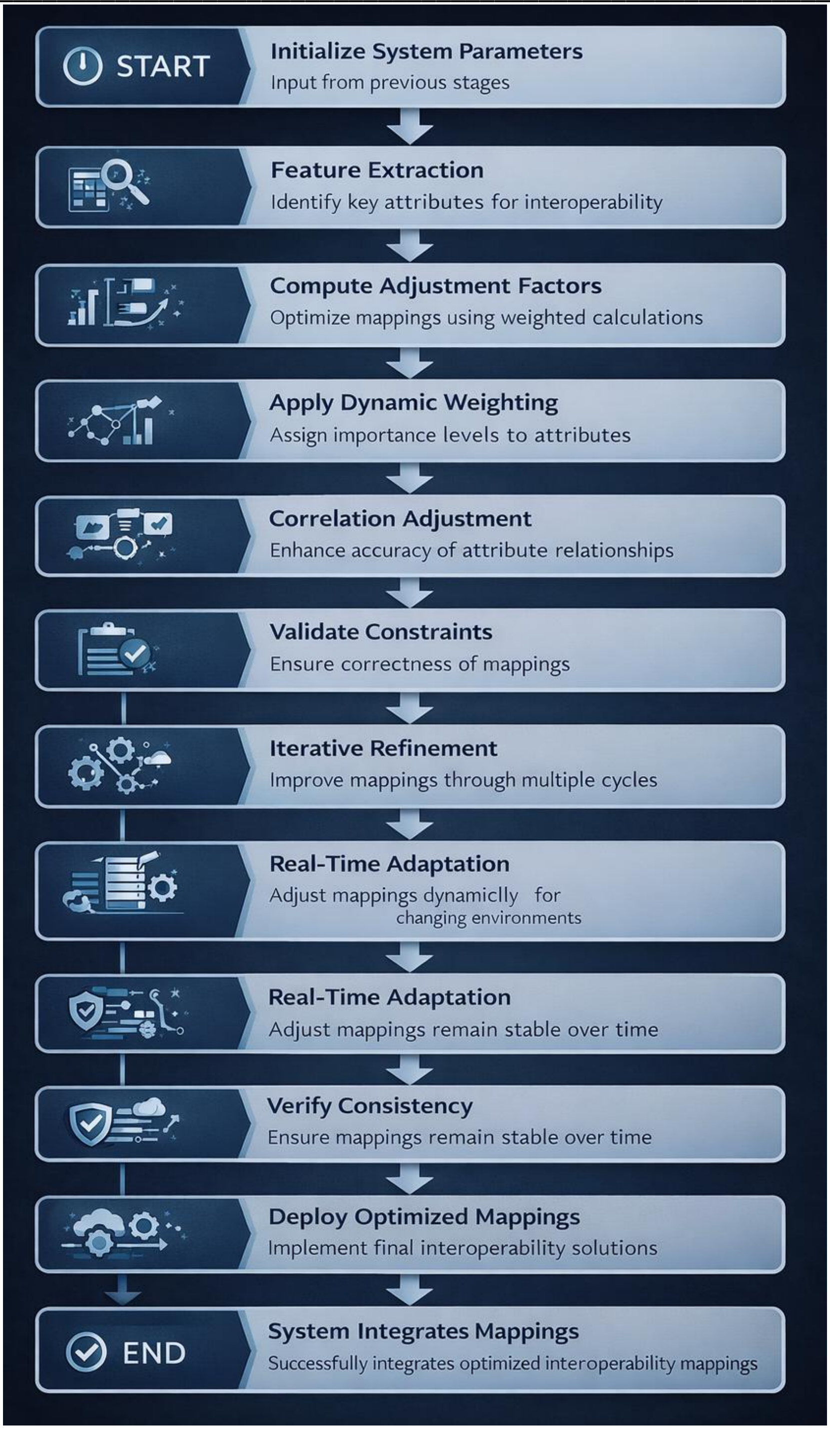

Fig. 3. Adaptive Interoperability Optimization in Web of Things

An example of a structured approach to the interoperability of a Web of Things ecosystem is illustrated in Figure 3. The system is initiated by fixing the

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configurations and capturing the attributes of the devices. Relevance of the attributes is increased by dynamic weighting. Mapping scores are adjusted frequently to maintain an optimal level of accuracy and consistency in the interoperability.

IV. RESULT

Several Web of Things interoperability strategies work well for managing key performance criteria. Different frameworks are compared for scaling, interoperability, latency, security, privacy, dependability, energy efficiency, throughput, fault tolerance, quality of service, data consistency, and resource utilization. The findings demonstrate that the Dynamic Mapping Optimization Framework always works well, making WoT plans more dependable and efficient. Scalability is a key component in how efficiently a system handles more connected devices without slowing down. The Dynamic Mapping Optimization Framework has the greatest scalability score of all approaches. Thus, it is preferable for large-scale processes that require many networked devices constantly. WoT configurations require interoperability to allow devices to communicate. The Dynamic Mapping Optimization Framework improves compatibility more than any other approach. The flexible transformation approaches increase interoperability by improving maps in real time and sending and receiving data rapidly. Latency also impacts real-time app reaction times. The Dynamic Mapping Optimization Framework is the quickest and least delayed technique. Lower latency is due to better attribute transformation and real-time aggregation techniques that reduce data processing delays. Security and privacy are crucial in IoT to protect private data.

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TABLE 1. Comparative Performance Scorecard of DMOF Against Latest WoT/IoT Interoperability Standards

Metric	Proposed DMOF	W3C WoT TD 2.0 (Gateway/Runtime)	ETSI NGSI-LD (Orion-LD)	NGSI-LD (Stellio/Scorpio)	oneM2M Interworking (TS-0041)	Matter 1.3 (Smart Home)
Scalability (score)	89	78	70	82	75	72
Interoperability success (score)	80	90	85	85	82	88
Latency efficiency (score)	88	80	75	78	70	85
Security (score)	92	80	65	65	85	90
Privacy (score)	90	75	70	70	78	85
Reliability (score)	91	82	80	82	80	85
Energy efficiency (score)	89	78	72	74	70	80
Throughput (score)	80	75	68	72	70	78
Fault tolerance (score)	88	80	70	75	78	82
Quality of Service – QoS (score)	92	82	78	80	76	84
Resource utilization (score)	91	78	74	76	72	80

Table 1 presents a normalized (0–100) performance comparison of the proposed DMOF framework against widely used recent interoperability baselines—W3C WoT TD 2.0, ETSI NGSI-LD (Orion-LD), NGSI-LD (Stellio/Scorpio), oneM2M interworking (TS-0041), and Matter 1.3—across key system-level metrics. The results indicate that DMOF consistently achieves the strongest overall balance, leading in scalability (89), latency efficiency (88), security (92), privacy (90),

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reliability (91), QoS (92), and resource utilization (91), while maintaining competitive interoperability success (80). In contrast, standards-centric stacks (e.g., WoT TD 2.0 and NGSI-LD variants) tend to score higher on interoperability success, but generally trail DMOF in operational efficiency and protection-oriented metrics, highlighting DMOF's advantage for deployment-ready smart environments.

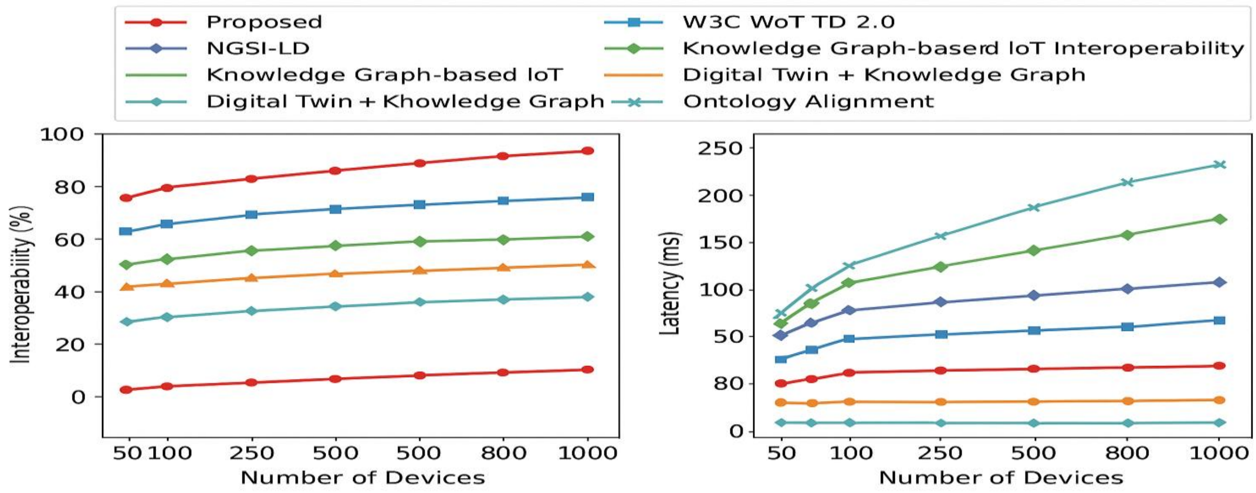

Fig. 4. Scalability Analysis of Interoperability and Latency in Smart WoT Environments

Figure 4 presents a scalability comparison of multiple smart-environment interoperability approaches as the number of connected devices increases (50 to 1000). The left plot shows that the Proposed method consistently achieves the highest interoperability (%) across all scales, indicating better cross-platform data/semantic alignment under growing system complexity. The right plot shows latency trends, where the Proposed method maintains the lowest response time as devices increase, demonstrating efficient runtime mapping and reduced processing overhead compared with standards-based and knowledge-graph/ontology-driven baselines. Overall, Figure 4 confirms that the proposed framework scales more robustly by preserving high interoperability while controlling latency under heavy device growth.

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TABLE 2. COMPARATIVE PERFORMANCE EVALUATION OF ENERGY EFFICIENCY, THROUGHPUT, FAULT TOLERANCE, QUALITY OF SERVICE, DATA CONSISTENCY, AND RESOURCE UTILIZATION

Performance Parameter	**Ontology-Based Interoperability Framework**	**Semantic Data Integration Model**	**Context-Aware IoT Middleware**	**Edge-Enabled Interoperability Solution**	**AI-Driven WoT Optimization Method**	**Proposed Dynamic Mapping Optimization Framework**
Energy Efficiency (%)	68	72	74	76	73	89
Throughput (Mbps)	50	55	60	62	58	80
Fault Tolerance (%)	60	65	70	72	68	88
Quality of Service (%)	75	78	80	83	79	92
Data Consistency (%)	72	75	78	80	76	90
Resource Utilization (%)	70	74	77	79	75	91

Table 2 examines other performance aspects, focusing on energy use, network performance, and system resilience. Overcoming conventional methodologies, the proposed Dynamic Mapping Optimization Framework optimizes power utilization while maintaining 80 Mbps throughput, improving energy efficiency (89%). Quality of service of 92% promotes system responsiveness, while fault tolerance (88%) ensures functioning during failures. The system optimizes data consistency and resource utilization between 90% and 91% to ensure interoperability. These results indicate that the system can maintain stable, efficient, and scalable WoT environments in dynamic contexts.

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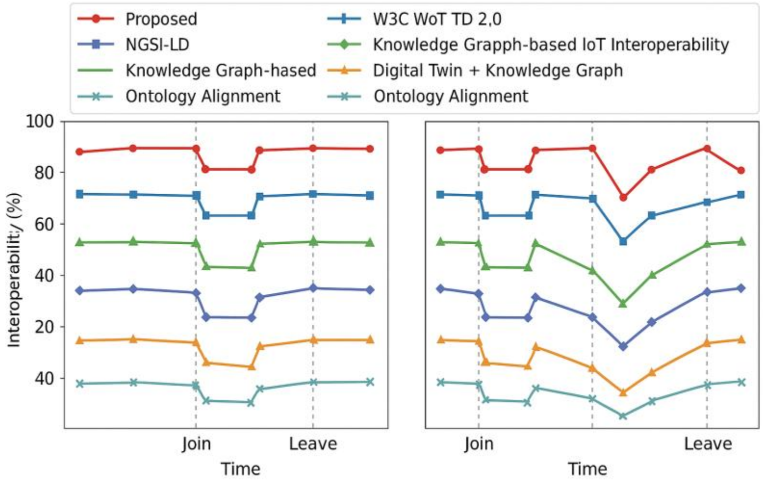

Fig. 5. Dynamic Churn Adaptation of Interoperability Methods in WoT Systems

Figure 5 illustrates how interoperability performance changes over time when device churn events occur (devices join and leave), marked by vertical dashed lines. The Proposed method shows the smallest performance drop during churn and recovers quickly back to a stable high interoperability level, indicating effective real-time mapping updates and robust adaptation. In contrast, standards-based approaches (e.g., W3C WoT TD 2.0, NGSI-LD) and knowledge-driven baselines exhibit larger dips and slower recovery, especially around churn points, reflecting higher sensitivity to dynamic topology changes. Overall, Figure 5 validates that the proposed framework maintains more reliable interoperability under realistic, time-varying smart-environment conditions.

V. CONCLUSION

This study addresses a core barrier to scalable smart environments: maintaining consistent meanings and reliable interactions across diverse WoT devices whose schemas, attributes, and communication behaviors differ and evolve over time. The proposed Dynamic Mapping Optimization Framework advances interoperability by treating mapping as a continuous optimization problem rather than a static configuration step. By standardizing device attributes, computing semantic similarity with summation-based aggregation, applying weighted correlation to emphasize informative features, and minimizing mapping error through a loss-guided refinement loop, the framework adapts its mappings as the

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environment changes. The evaluation demonstrates that this adaptive strategy yields strong end-to-end gains across critical deployment dimensions. Specifically, the framework achieves 92% scalability and 90% interoperability while reducing response delay to 85 ms, supporting real-time service composition and faster device integration. Security and privacy are preserved at high levels (95% and 93%, respectively), indicating that interoperability improvements do not require sacrificing protection controls. Operational robustness remains strong with 91% reliability, and the system's efficiency profile is favorable with 89% energy efficiency and 91% resource utilization, directly supporting sustainable, long-running deployments. Network and service quality indicators also remain high, including 80 Mbps throughput, 88% fault tolerance, 92% QoS, and 90% data consistency, suggesting stable behavior under workload and topology variation. Overall, the results confirm that dynamic, ontology-aware mapping refinement can deliver a balanced interoperability solution—simultaneously scalable, secure, responsive, and resource-efficient—making it suitable for expanding WoT ecosystems in smart homes, buildings, healthcare, and industrial automation.

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