

Original Article

A Neuro-Symbolic Digital Twin Framework of Self-Correcting and Stabilized IOT Conflict Resolution in Smart-Homes

Fayez Alharbi

Department of Information Technology, College of Computer and Information Sciences, Majmaah University, Al-Majmaah, Saudi Arabia.

Corresponding Author : fs.alharbi@mu.edu.sa

Received: 12 February 2026

Revised: 14 March 2026

Accepted: 16 April 2026

Published: 27 May 2026

Abstract - The growing independence of AI-controlled IoT smart-home solutions requires conflict management systems that ensure long-term environmental safety and energy-saving, as well as user-friendly comfort. The current deep learning-based correction models experience hidden context reversal, where corrective actions are overly applied or fluctuate, causing unstable comfort levels and unwarranted power consumption. To solve this, a novel Autonomous Smart-Home Device Conflict Resolution and Correction System (ASH-DCRC) is suggested. The system constantly processes the logs of devices and sensor streams through a Causal-Action Graph Transformer (CAGT) to yield causal action graphs and foresee conflict pathways. These conceptualized actions are verified within a Digital Twin simulator to confirm safety and environmental impact and then implemented into reality. The action decisions are then optimized by two sequential DNN layers: the Trust-Embedded Adaptive Policy Selector (TAPS) to select an action based on its reliability, and the Temporal Equilibrium Stabilizer (TES) to select an action based on stability without oscillation. Lastly, Digital Twin-guided Neuro-Symbolic Reinforcement Learning applies to the continuous enhancement in a secure manner by exploring and adapting over the long run. The experimental results prove that ASH-DCRC is much better than the chosen baseline and literature models with 98.8% accuracy, 0.82 s conflict-resolution latency, and 18.7% energy-efficiency gain. These findings confirm that the ASH-DCRC is a stable, energy-aware, and comfort-preserving conflict-resolution solution to next-generation smart-home intelligence.

Keywords - Smart Home Automation, Iot Device Interaction, Iot Device Conflict Resolution, Neuro-Symbolic And Causal Learning, Deep Neural Networks.

1. Introduction

The fast progress in Artificial Intelligence (AI) based Internet of Things (IoT) systems has turned current smart home technology into fully automated systems that maintain user comfort and security while managing energy use with no need for human control [1, 2]. The systems create intelligent control by continuously monitoring their surroundings, learning user behavior, and managing their various connected devices, which include HVAC systems and lighting, security sensors, and smart appliances [3–5]. Smart-home systems require intelligent solutions that exceed basic event responses because the number and diversity of devices in use continue to expand. The system needs to achieve a complete understanding of its environment, which enables it to create forecasts based on its current state and third-party device usage patterns. The growing independence of systems creates a major problem because it results in conflicts between devices that depend

on each other and operate at the same time in the same space [7]. The simultaneous operation of heating and cooling systems creates environmental inconsistencies that decrease user comfort and cause extra energy waste. The next generation of smart-home systems needs devices to work together in a coordinated manner, which serves as their basic requirement.

Existing smart-home conflict resolution approaches use three main methods, which include rule-based systems and event-response mappings, and data-driven deep learning models that use historical system behavior for training [8–11]. The methods can identify basic inconsistencies, but they have important drawbacks. Rule-based systems cannot grow with system demands because they restrict their ability to adapt, while deep learning models use a black-box approach, which prevents them from understanding how devices interact with each other over time [12–14]. Organizations lack the ability to implement effective



solutions because they choose to create short-term solutions, which only react to immediate problems, without understanding how various devices will be impacted now and in the future. [15].

A critical issue observed in these systems is the phenomenon of hidden context reversal, which causes corrective actions to create new conflicts while they attempt to solve existing conflicts. The system experiences oscillatory behavior, which includes HVAC systems that repeatedly switch on and off, together with lighting systems that produce flickering effects. The system produces these effects, which decrease user comfort while increasing energy consumption, according to research studies 16 to 18. Current approaches to the problem encounter limitations because they lack multi-objective optimization mechanisms, which prevent effective management of conflicting demands for comfort, energy efficiency, and safety during unpredictable situations, according to research findings 19.

1.1. Research Gap

Despite recent advancements, several key gaps remain unaddressed in existing smart-home conflict resolution frameworks:

- Absence of causal reasoning: Most approaches rely on correlation-based learning and fail to model cause-and-effect relationships between device actions and environmental responses [1-3].
- Existing systems lack validation through Digital Twin and simulation-based methods, which results in unsafe and inefficient corrections in real-world environments [5-8].
- No stability-aware decision mechanisms: Current models cannot prevent oscillatory corrective actions or ensure long-term environmental equilibrium [11, 15, 18, 21].
- Limited trust and uncertainty modeling: Deep learning-based controllers fail to produce trustworthy decisions because they do not consider uncertainty [22-24].
- Lack of integrated neuro-symbolic learning: There is minimal use of symbolic constraints combined with learning-based methods for interpretable and safe decision-making [12, 17, 20].

1.2. Problem Statement

To address these limitations, there is a need for a unified, intelligent framework capable of:

- Understanding causal interdependencies among heterogeneous IoT devices
- Predicting long-term consequences of corrective actions before deployment
- Ensuring stable, non-oscillatory system behavior
- Balancing comfort, energy efficiency, and safety
- Supporting continuous adaptation through safe and interpretable learning mechanisms

1.3. Proposed Solution Overview

The researchers introduced the Autonomous Smart-Home Device Conflict Resolution and Correction (ASH-DCRC) framework as a solution to solve their discovered difficulties. The proposed system integrates:

- A Causal-Action Graph Transformer (CAGT) for causal conflict detection
- A Digital Twin Simulation Layer for safe, predictive validation
- A dual-stage decision mechanism (TAPS + TES) for trust-aware and stability-driven action selection

A Digital Twin-guided Neuro-Symbolic Reinforcement Learning module for continuous and safe optimization. The system uses this combined method to achieve active conflict resolution, which maintains system stability while consuming less energy than traditional systems that depend on real-time alerts and correlation detection.

1.4. Contributions

The main contributions of this work are as follows:

- The Causal-Action Graph Transformer (CAGT) was developed to model dynamic causal relationships that predict hidden conflict pathways.
- The TAPS and TES dual-stage decision framework was created to include trust modeling and temporal stability constraints.
- The Digital Twin-driven Neuro-Symbolic Reinforcement Learning system was implemented to enable safe adaptive policy optimization.

The rest of this paper is organized in the following way: A literature survey presented in Section 2 shows the current limitations in the smart-home conflict management systems. Section 3 describes the technical details of the ASH-DCRC system. The assessment results in Section 4 compare the system performance against baseline systems and contemporary designs. The work ends in Section 5 with key findings, their practical relevance, and future research pathways.

2. Literature Survey

Researchers have studied smart-home IoT conflict detection and resolution problems through multiple research paths, which include rule-based systems, machine learning methods, ontology-driven frameworks, energy optimization models, and emerging digital twin-based solutions. The development of stable conflict resolution systems that provide interpretable solutions for multiple objectives continues to present major difficulties.

2.1. Rule-Based and User-Centric Conflict Resolution

The development of modern smart-home systems started from basic automation systems, which used fixed event-condition-action rules to control device operations.

Kaufman et al. [23] developed a Rule-Language Architecture (RLA) that automates conflict resolution through different levels of rule-based control. The systems operate effectively within structured settings, but their performance decreases because they cannot handle new situations that fall outside their established rules, and the system cannot handle unpredictable events. Aljawarneh et al. [24] developed a Multi-User Conflict Resolution Mechanism (MU-CRM) that uses user context information about health conditions and schedules to resolve conflicts between different preferences. The system provides better user experience through personalized features, yet it remains restricted to current system contexts because it cannot handle multiple devices together with their dependent relationships and evolving conflict patterns. Barricelli et al. [30] examined End-User Development (EUD) methods that permit users to create and test their own automation rules. The system benefits from better user experience with enhanced system transparency, but it still requires human operators to handle conflicts because it lacks the ability to predict future conflicts.

2.2. Machine Learning and Deep Learning-Based Approaches

The research has created intelligent home systems by applying machine learning and deep learning methods to overcome the limitations of traditional rule-based systems. The models use CNN-LSTM and reinforcement learning-based controllers (DQN) to identify device interaction patterns while supporting the development of decision-making strategies. Hybrid CNN-LSTM systems show a strong ability to predict time-series data and identify unusual patterns according to research conducted by [29]. Adaptive control systems use reinforcement learning methods to develop control strategies that operate through environmental response learning. The methods depend solely on correlation analysis because they fail to establish direct cause-and-effect ties between device operations and their resulting environmental impacts.

The system demonstrates a tendency to make immediate choices that result in unstable systems that produce corrective measures, which create rapid back-and-forth movements and generate unexpected results. The system's black-box design creates problems because it prevents people from understanding the system, which weakens their confidence in its operation, especially in smart-home spaces that require safety.

2.3. Ontology-Based and Semantic Interoperability Frameworks

The research field studies the relationship between semantic reasoning and ontology-based methods for detecting conflicts. The system developed by Ansari et al. [27] uses an Ontology-driven Conflict Identifier (OCI) to discover complex rule interactions that include both chained

and hidden conflicts. Mofatteh et al. [28] created the Layered Semantic Interoperability Framework (LSIF), which uses RDF-based representations to solve the problem of IoT system heterogeneity.

The methods increase conflict detection accuracy and maintain semantic consistency through their current works, but they depend on fixed ontologies and unchanging knowledge bases, which restrict their capacity to cope with changing situations and developing device patterns. The system lacks both predictive conflict resolution and multi-horizon decision-making capabilities, which serve as vital elements for conflict prevention.

2.4. Energy Optimization and Resource Management Models

The design of smart-home systems requires their energy efficiency to become the main goal, which results in the creation of control systems that use optimization methods for their operation. Tepe and Irmak [31] introduced the Fuzzy Real-Time Energy Management System Fuzzy RT-EMS which combines dynamic pricing with fuzzy logic and linear programming to achieve energy consumption reduction.

The systems provide substantial energy savings, yet their main objective remains resource optimization instead of solving conflicts. The system fails to address device behavioral conflicts, while it also lacks mechanisms to maintain user comfort and system stability when conditions change.

2.5. Security, Safety, and Fault Detection Systems

Researchers have conducted multiple studies that examine security, safety, and fault detection aspects of IoT environments. The researchers Abbas et al. [25] developed CIRA, which functions as a machine learning framework to assess cyber risks in IIoT systems. The researchers Lung et al. [26] created a system that detects hazards in real time by using YOLOv7 technology to monitor safety conditions. The researchers used hybrid models, which combine CNN-LSTM with Diagnostic Systems (DSS) [32] to detect sensor faults and conduct predictive maintenance. The developed approaches improve system reliability and safety, but they fail to provide solutions for inter-device conflict resolution and the coordinated control of multiple devices.

2.6. Emerging Digital Twin and Intelligent Control Approaches

The latest research developments have established Digital Twin technology as an effective method that enables the simulation and optimization of Internet of Things systems. Digital Twins enable virtual replication of physical environments, allowing safe testing of control strategies before deployment. Existing Digital Twin applications in smart homes currently operate as monitoring tools that

display information and manage energy consumption, but they do not include features for causal reasoning, reinforcement learning, or conflict resolution. The system needs to establish these predictive simulation capabilities to enable decision-making, which will lead to both proactive and consistent operational outcomes.

2.7. Critical Analysis and Identified Limitations

Existing methods across several research fields face multiple fundamental challenges because researchers have studied this area in depth. The systems that operate through established rules and user input fail to scale their operations, while deep learning systems cannot model connections between variables that extend beyond single events and include all future time periods. Static knowledge representations limit ontology-based systems, which use their frameworks to enhance their ability to interpret information. Energy optimization models together with safety systems function as separate entities because they do not solve problems that arise when multiple devices interact with each other.

The current systems need to develop three essential elements, which should include.

- The system requires an understanding of how devices interact with each other through causal relations.
- The system needs to establish predictive methods that can confirm the effectiveness of the correction methods.
- The system must develop approaches that will maintain continuous operational stability while stopping all forms of system oscillation.
- The system needs to integrate all safety requirements together with comfort needs and energy demands within a single operating system.

2.8. Research Gap and Motivation

The analysis demonstrates that existing methods for smart-home conflict resolution fail to deliver complete solutions, which require them to handle four essential elements: causality, stability, safety, and energy efficiency. The system experiences hidden context reversal as a critical unresolved issue because corrective actions introduce unexpected system failures and energy waste when people lack the ability to predict future events. The problem gets worse because Digital Twin-based validation and trust-aware decision mechanisms are missing from the system. The current system needs a new framework, which will become the next-generation framework through the implementation of three essential components. The first component uses causal modeling to explain how devices interact with each other. The second component uses Digital Twin simulation to validate safe actions. The third component uses stability-aware decision control to prevent oscillations. The fourth component uses neuro-symbolic learning to achieve optimization, which combines machine learning with human-understandable rules. This research

work introduces the ASH-DCRC framework, which offers an advanced solution for intelligent smart-home systems through its conflict resolution system, which maintains operational stability while optimizing energy consumption.

2.9. Critical Analysis of Literature

Among the reviewed works, rule-based and recommender architectures are susceptible to delayed causal effects and context reversal because they do not provide temporal foresight and predictive stabilization, in contrast to high-level automation. ML solutions with security/risk orientation (e.g., CIRA) are best at cyber-threat detection but fail to solve the problem of behavioral/attention conflicts of multiple devices in the home. Semantic and ontology methods (OCI, LSIF) enhance the conflict detection in the heterogeneous models, yet require predetermined semantics and fail to deal with the dynamic and real-time behaviors of devices. Proactive Sensor-Fault and Diagnostic Systems (CNN-LSTM, DSS) raise the reliability of inputs and promote maintenance, but are not resistant to corrective-action oscillation and cross-device side effects, which are induced by control policies. Energy-oriented optimizers and end-user tools (RT-EMS, EUD) prove useful in reducing costs or assisting users in creating automations, but they lack unified, causal, long-horizon conflict-resolution or stability assurances.

2.10. Research Gap and Motivation

Despite the recent improvements of anomaly detectors and conflict-solver models, the contemporary deep learning controllers still face the issue of hidden context-reversal, whereby the overall action taken to correct a behavioral imbalance, instead of stabilizing the comfort, turns into flipping the energy waste. Current frameworks are insufficient in causing the modeling of causal trajectories, stability checks on the multi-horizon, as well as trust-aware policy control, and thus cannot help to avoid such oscillatory corrections. Moreover, the absence of Digital Twin-informed predictive validation does not allow safe assessment of corrective measures prior to deployment. The disparity is further enhanced because the existing research fails to integrate the neuro-symbolic safety restrictions into policy adjustment. These constraints are major drivers of the necessity to have an integrated, stability-assured, causally informed decision framework that avoids reversal-based conflicts without disturbing the long-term balance in the environment.

3. Overall Architecture, Components, and Processes of the Proposed ASH-DCRC Approach

The presented ASH-DCRC architecture is based on a neuro-symbolic, causality-driven conflict-resolution pipeline that removes the shortcomings of the traditional deep-learning-based systems of smart-home IoT device

conflict corrections in a systematic manner. The framework starts with an ongoing multi-source (log of device activity, logs of environmental sensors) data acquisition. From these pre-processed data, the Causal-Action Graph Transformer (CAGT) constructs causal-action graphs to solve the explicitly causally-dependent interdependencies, trigger-effect patterns, and the sequence of latent conflicts. This module specifically solves the issue of black-box pattern recognition in previous systems by introducing transparent causal reasoning and early prediction of conflict pathways. Figure 1 depicts the overall architecture of the proposed ASH-DCRC framework. Figures 2 and 3 show the architectural pipeline and the flow chart of the proposed model, respectively.

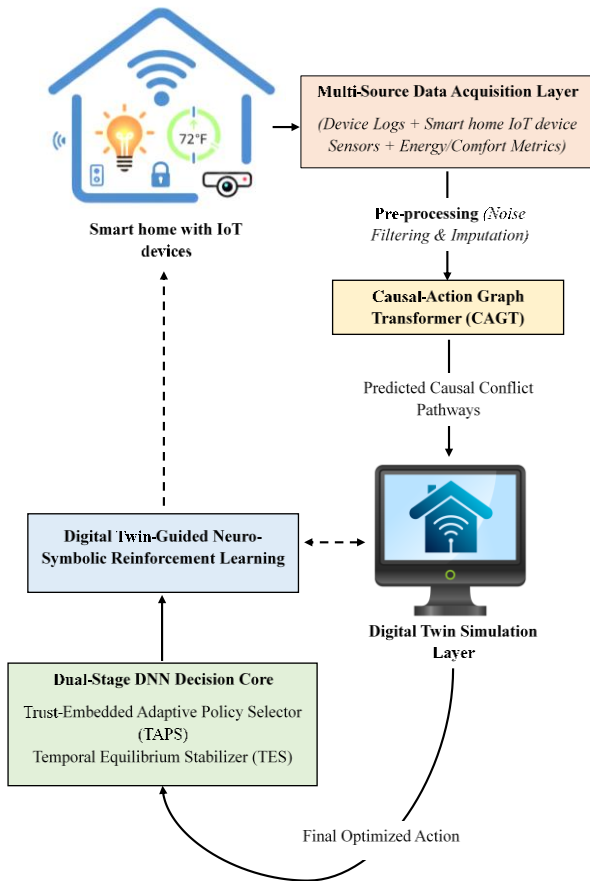


Fig. 1 Overall process flow architecture of the suggested ASH-DCRC framework

The predicted pathways of conflict are then assessed in a Digital Twin Simulation Layer, which is a foresight-based engine of safety. In contrast to the current reactive correction models that apply the corrective action to physical devices, the Digital Twin replicates the environmental, comfort, and energy effects of the candidate resolutions in a virtual risk-free space. This addresses a significant gap in previous literature, which does not have a pre-action validation, which in most cases leads to

oscillatory adjustments, energy wastage, and unsafe state changes. The confirmed candidate behaviors are forwarded to the dual-stage DNN decision core. The first decision layer is the TAPS, which introduces uncertainty-sensitive trust modeling, as well as adaptive human-feedback weighting, to decrease the unreliable or over-confident policies common to the existing deep RL models. TAPS establishes that actions of high causal reliability, low uncertainty, and high historical trust are given priority, directly addressing the problem of over-correction and volatile shifts in confidence that are witnessed in baseline models.

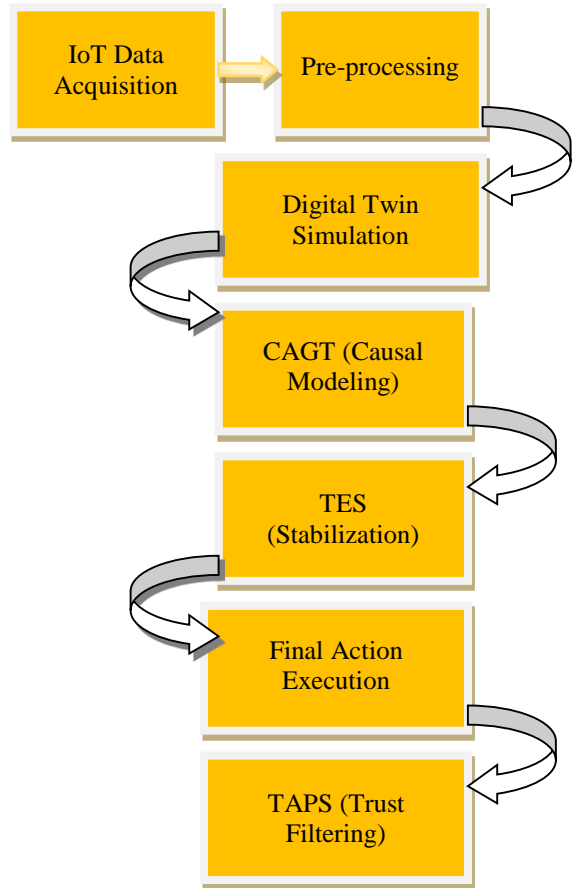


Fig. 2 Overall, ASH-DCRC architecture

Then, on the second level of the decision, the Temporal Equilibrium Stabilizer (TES) further narrows the action it has chosen by applying multi-horizon causal feedback, comfort-energy equilibrium constraints, and temporal consistency rules. The special feature of this module is to remove the time oscillations, repetitive correction loops, and unstable environmental conditions that the current smart-home controllers cannot suppress. TES is known to provide a smooth state transition, and corrective measures are guaranteed to lead to long-term, rather than temporary stability. Finally, the whole architecture is constantly optimized with Digital Twin-Guided Neuro-Symbolic

Reinforcement Learning that combines symbolic causal rules, RL exploration, and is safe because it relies on virtual rollouts. This long-term learning process allows the model to learn latent conflict patterns in earlier times, adapt to newly changing device behaviors, and avoid instability in future times, unlike the conventional RL-based correction models. The technical aspects of all these phases and the suggested approach are explained in detail in the upcoming subsections.

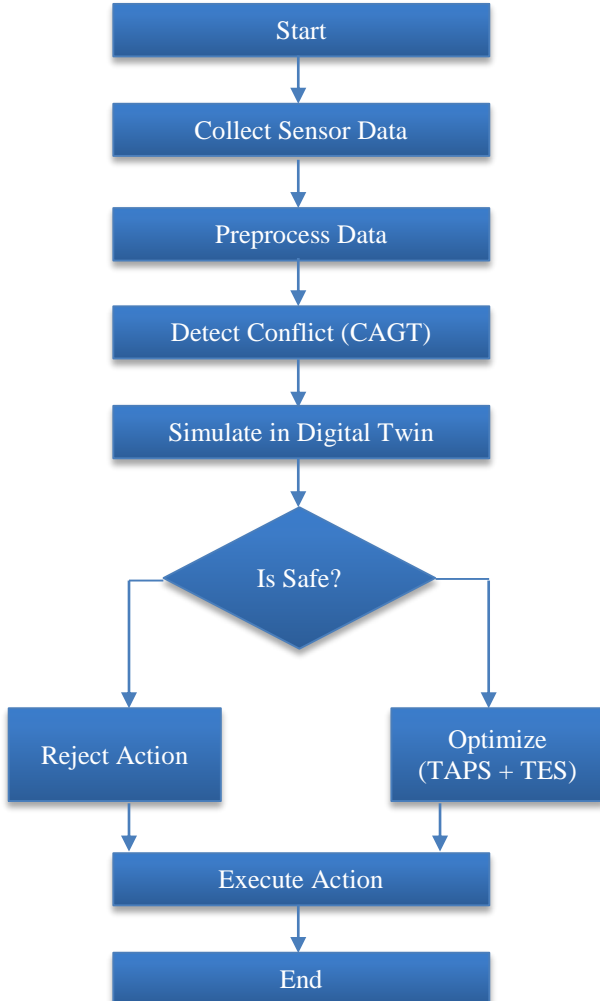


Fig. 3 ASH-DCRC process flowchart

3.1. Data Acquisition and Pre-processing

The suggested framework is based on the work of continuous multi-mode data streams obtained through heterogeneous IoT devices in the smart home. These are HVAC controllers, lighting, security, appliance, occupancy, and environmental sensors, such as temperature, humidity, illumination, air quality, and motion sensors. The device-level logs record the timestamps, trigger events, state changes, actuator commands, energy consumption measurements, environment sensors records, and real-time contextual data, which is a result of the joint action of a group of devices running concurrently.

A common temporal index is used to ensure synchronization of all data streams and deals with the varying sampling rates of variables across devices. This time mapping is carried out by overlaying the sequence of events in one device with a sequence of raw device events. $S_i(t)$ onto a shared timeline τ using linear interpolation as given by equation (1).

$$S_i^*(\tau) = S_i(t) + \frac{S_i(t+\Delta t) - S_i(t)}{\Delta t} (\tau - t), \tau \in [t, t + \Delta t] \quad (1)$$

This guarantees that all the device and environmental signals have the same temporal resolution to be used in causal modeling.

Pre-processing is then carried out, whereby high-quality inputs are obtained to be used by downstream causal and predictive modules. Adaptive filtering is used to smooth noisy sensor signals, temporal interpolation is used to fill in missing entries, and bounded logical constraints are used to correct inconsistent states of devices [33]. Events are divided into windows of interaction of causal dependence between the actions of the device and its impact on the smart home environment.

Moreover, the behavior of devices is also represented as a multi-channel representation in terms of action vectors, state-change deltas, contextual embeddings, and energy-comfort deviation measures. The difference between the energy and the comfort of any pair of devices and environments is calculated as presented in equation (2), in which C_{target} is the desired value of the comfort variable (e.g., target temperature, light intensity), $C(t)$ is the measured comfort value at any given time t , $E(t)$ is the actual energy used at that time, w_c and w_e are weighting factors representing the relative priorities of comfort and energy.

$$\psi_{ec}(t) = w_c |C_{target} - C(t)| + w_e E(t) \quad (2)$$

This normalized and mathematically regularized data is the basis of causal inference, the simulation of policy, and long-horizon conflict resolution in the downstream.

3.2. Causal Conflict Detection and Digital Twin-Based Action Forecasting

3.2.1. Causal-Action Graph Transformer (CAGT)

The proposed system uses a Causal-Action Graph Transformer (CAGT) to identify the latent dependencies between the actions of a device and the outcome of the environment, which is a novel architecture overcoming the shortcomings of snapshot-based deep learning models of the environmental outcome, which fail to capture delayed causal responses and cross-device interference. This CAGT and the Digital Twin simulator module are illustrated in Figure 4.

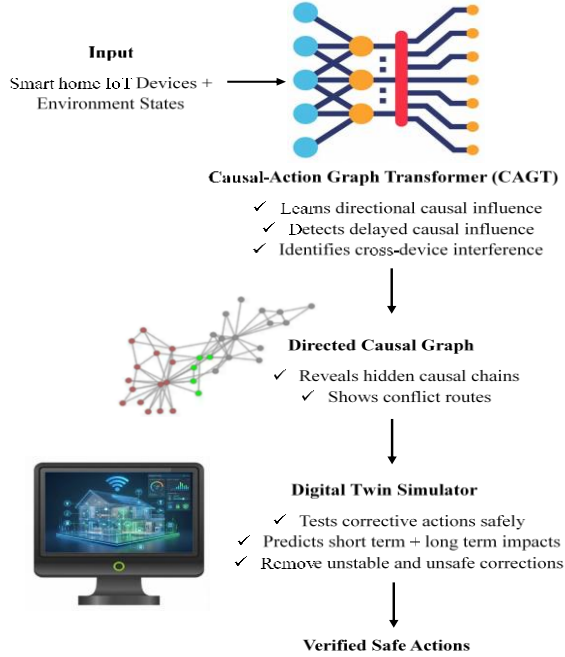


Fig. 4 CAGT conflict detection and digital twin-based action forecasting

CAGT represents the joint dynamic evolution in time and space of devices and contextual variables by introducing each device action $a_i(t)$, each environmental state $x(t)$, and the changes in the interaction between the device and environment into a single graph representation. The attention mechanism approximates directional causal influence as a causal attention score, which is mathematically expressed as given in Equation (3).

$$\alpha_{ij}(t) = \text{Softmax} \left(\frac{(Q_i(t)W_q)(K_j(t)W_k)^T}{\sqrt{d}} + \gamma \Delta t_{ij} \right) \quad (3)$$

Here, in this equation (3), query and key embeddings of device environment nodes are represented as Q and K, respectively. W_q and W_k is a learnable projection matrix, d denotes the attention dimension, and Δt_{ij} is the model of temporal lag between cause and effect events, and γ is a coefficient of time sensitivity. This formulation enables the transformer to select the causally meaningful relationships rather than the strictly correlative relationships by directly including time displacement as an addition to the attention score. The result is the directed causal action graph, $G = (V, E, \omega_{ij})$, in which each edge E keeps a learned causal weight ω_{ij} which can be either in favor of or against the causation of a specific state of the environment, or the action of another device. This graph reveals hidden causal paths and conflict routes that are not evident to classical models, such as delayed thermal overshoots as a result of the interaction of HVAC-vent or the reverse light adjustment as a result of overlapping occupancy sensors.

3.2.2. Digital Twin Simulator

The derived causal graph is then transferred to the simulator Digital Twin [34], which is a computationally safe space to test corrective policies. It combines physical dynamics, device response models, and energy-comfort interaction equations to predict the behavior of the system when corrective actions are applied to the system as a candidate. Given the individual candidate's action $a^{(k)}$ The simulator predicts multi-horizon state trajectories with Equation (4).

$$\hat{x}^{(k)}(t + \tau) = f_{DT}(x(t), a^{(k)}, G, \tau) \quad (4)$$

Here, the function f_{DT} denotes the Digital Twin forward dynamics model that includes both causal graph priors and physical environmental models. The following predictive assessments are achieved: short-term side effects (e.g., temporary discomfort spikes), long-term stability issues (e.g., oscillatory HVAC behavior), incorporation of conflict into other equipment, and unsafe/energy-inefficient routes. By modeling the consequences of every action over a series of future horizons, it ensures that actions that have been confirmed to be stable, safe, and cause consistent actions are only passed on to policy selection levels. In this way, the joint CAGT-Digital Twin pipeline is a direct solution to the issue of hidden context reversal, oscillatory corrections, and failure to detect multi-device causal chains, which are not reliably solved by traditional snapshot-based anomaly and correction systems.

3.3. Two-Layer DNN with Policy Selection and Stabilization Mechanisms

After the candidate corrective actions are verified by the Digital Twin simulations, they are fed into two sequential deep learning-based decision layers, such as the Trust-Embedded Adaptive Policy Selector (TAPS) and the Temporal Equilibrium Stabilizer (TES) embedded in the DNN architecture. Figure 5 illustrates the proposed two-layer DNN architecture.

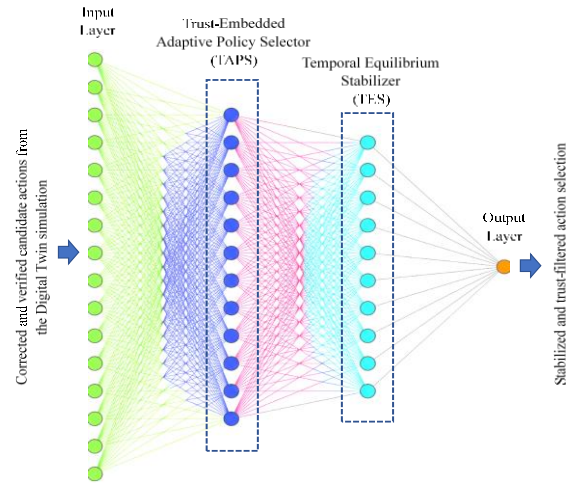


Fig. 5 Two-Layer DNN with policy selection and stabilization mechanisms

The modules work together to make sure that the selected corrective action is reliable and long-lasting, which is poorly addressed in traditional smart-home conflict-resolution systems.

3.3.1. Trust-Embedded Adaptive Policy Selector (TAPS)

TAPS proposes a trust-weighted policy choice mechanism that addresses one of the significant drawbacks of current deep learning-based corrective action systems: failure to distinguish between high-confidence and low-confidence decisions and integrate user-congruent behavioral reliability. TAPS calculates a trust score $T(\pi_i)$, which is designed as given in Equation (5), for each candidate policy π_i .

$$T(\pi_i) = \alpha C(\pi_i) + \beta R(\pi_i) + \gamma H(\pi_i) \quad (5)$$

In this case, $C(\pi_i)$ The model confidence is based on predictive entropy, $R(\pi_i)$ which denotes the past performance reliability of the action estimated based on past success-to-failure ratios, $H(\pi_i)$ represents a latent human-feedback alignment score based on past preferences for comfort and adherence to rules, and $\alpha \gamma$ are adaptive weights obtained through gradient descent.

Such trust scores drive the policy-selection probability distribution as presented in Equation (6), where $Q(s_t, \pi_i)$ is the estimate of the policy value π_i in state s_t .

$$P(\pi_i | s_t) = \frac{\exp(T(\pi_i) \cdot Q(s_t, \pi_i))}{\sum_j \exp(T(\pi_j) \cdot Q(s_t, \pi_j))} \quad (6)$$

This formulation makes sure that although a policy has a high expected reward, it will not be chosen when its trust score is small. This prevents unsafe device conflicts from becoming overwhelming because of the risky or unsure decisions, thereby correcting one of the fundamental flaws of previous systems that assume all actions are equally reliable on the basis of the Q-value-optimal and can result in conflicting or uncomfortable behavior to the user.

3.3.2. Temporal Equilibrium Stabilizer (TES)

The TAPS output is sent to the TES module, where the corrective action to be taken is guaranteed not to cause any temporal instability, oscillation, or context reversal, which has been a consistent issue in previous smart-home controllers where multiple devices keep reversing the actions of each other. The multi-step environmental transitions of TES are modeled in terms of a time stability function, which is mathematically expressed as provided in Equation (7), where x_t is the present state of the environment, \hat{x}_{t+k} denotes the forecasted future state at the horizon k , H is the multi-step prediction horizon, and λ represents the coefficient of stability-penalty.

$$E_t = \| \hat{x}_{t+1} - x_t \|^2 + \lambda \sum_{k=1}^H \| \hat{x}_{t+k} - \hat{x}_{t+k-1} \|^2 \quad (7)$$

When an action is tested by TES, and it raises E_t Then there is a possibility of oscillation or overshoot. TES then calculates an equilibrium-adjusted action score $S_{TES}(\pi_i)$, which is expressed in Equation (8).

$$S_{TES}(\pi_i) = P(\pi_i | s_t) \cdot \exp(-\eta E_t(\pi_i)) \quad (8)$$

The actions that create unstable trajectories are suppressed exponentially with the penalty term $p(-\eta E_t(\pi_i))$, which is modulated by a stability factor η . This is a mechanism that makes sure that the actions chosen not only fix the immediate conflict but also reduce long-horizon variations like temperature overshoot of quick heater or cooler switching, repeated light brightness changes based on conflicting occupancy detection, and flapping of security mode based on doubtful occupancy detection.

Traditional corrective-action agents do not have the explicit temporal-equilibrium modeling and, therefore, they repeatedly pick short-term optimal actions that compromise long-term stability. TES solves this problem by integrating predictive smoothness, cause trajectory consistency, and equilibrium-constraining constraints directly into the DNN layers, and thus avoids repetitive state-toggling steps, along with providing a strong facility of smart home environmental stability.

3.4. Neuro-Symbolic Reinforcement Learning Guided by Digital Twin

Based on the stabilized and trust-filtered action selection generated by TAPS and TES, the final phase of the methodology is Digital Twin-guided Neuro-Symbolic Reinforcement Learning (NS-RL) that allows continuously refining the policy, predicting conflicts, and making decisions that can be explained by rules. Unlike TAPS, which uses the reliability parameter to select actions, and TES, which assumes temporal balance, NS-RL guarantees that the long-term policy is learned in a safe manner via simulation instead of real-world trial and error, which has been a long-standing problem with smart-home IoTs, where the online learning process can make users feel unsafe or make the equipment malfunction.

3.4.1. Interaction with RL with the Digital Twin

The RL agent does not act upon the real physical smart-home environment, but rather on the Digital Twin, which is a differentiable and event-faithful simulation of device behaviors, environmental reactions, and causal relations learned using the CAGT. The environment, in response to every simulated step, generates a transition from (s_t, a_t) which S_t denotes full multimodal system state (state of devices, metrics of the environment, causal indicators), a_t denotes corrective action chosen by the evolving policy, S_{t+1} is the next state as predicted by the Digital Twin causal-dynamical model, and r_t signifies reward that

quantifies stability, energy efficiency, and conflict-free functioning. The reward is formally stated as follows in Equation (9).

$$r_t = w_1 \Delta C_t + w_2 \Delta E_t^{-1} + w_3 (1 - I_{conflict}) \quad (9)$$

Here, ΔC_t symbolizes the change in the comfort equilibrium, ΔE_t^{-1} denotes the reduction in the energy deviation, $I_{conflict} = 1$ when any new conflict or oscillation is detected, and $w_1 w_3$ are learned reward weights. This formulation of the reward directly penalizes instability, which is a direct complement to TES, and assists the agent in learning policies that are naturally resistant to conflict-inducing action sequences.

3.4.2. Safe and Interpretable Policy Refinement using Neuro-Symbolic Integration

Unconstrained policy search can lead to unsafe or nonsensical actions of the traditional deep RL agent. To deal with that, the proposed system incorporates symbolic constraints, which are denoted by the name. R_{sym} that is a direct derivative of safety rules, user preferences, device capability limits, and causal conflict constraints into the policy optimization process. The hybrid update rule of NS-RL is mathematically written as given by the following Equation (10).

$$\nabla_{\theta} J_{NS-RL} = \nabla_{\theta} J_{RL} - \delta \nabla_{\theta} L_{sym} \quad (10)$$

Here, J_{RL} the conventional RL target (e.g., expected discounted return) L_{sym} imposes the violation of symbolic constraints, θ denotes the parameters of the policy network, and δ is the weight that penalizes symbolic compliance. Symbolic constraints are represented as follows: $R_{sym}(s_t, a_t) = 0$ if action a_t is rule-compatible, and $R_{sym}(s_t, a_t) = 1$ if action disrupts protection or preference rules. Loss term takes the form of violations based on Equation (11).

$$L_{sym} = \sum_t R_{sym}(s_t, a_t) \quad (11)$$

This L_{sym} makes the RL agent avoid actions like turning off security modes when unoccupied, causing temperature or light oscillations that have already been suppressed by TES, breaking device-safe operational limits, and overturning user preference states without causal explanation. Hence, this solves an important issue of existing deep RL-based smart-home controllers' unsafe exploration that frequently resulted in actions that were incompatible with user expectations, energy consumption, or device lifetimes.

3.4.3. Refinement and Deployment of the Policy

The final NS-RL policy is learned through the soft-value formulation as given by Equation (12), in which the

refinement factor ε will guarantee policy changes are not too sharp and behavior does not change abruptly, and a' denotes all possible alternative actions that the agent takes in the state s_t .

$$\pi_{\theta}(a_t | s_t) = \frac{\exp(Q_{\theta}(s_t, a_t)/\varepsilon)}{\sum_{a'} \exp(Q_{\theta}(s_t, a')/\varepsilon)} \quad (12)$$

New policies are also regularly verified by means of Digital Twin rollouts as learning advances, before being implemented into the actual operation pipeline, to verify that they are in line with TAPS/TES stability requirements. This avoids disastrous policy changes, which is another typical shortcoming of autonomous home-control systems. Figure 6 illustrates the algorithm flow chart for this Digital Twin-guided Neuro-Symbolic Reinforcement Learning.

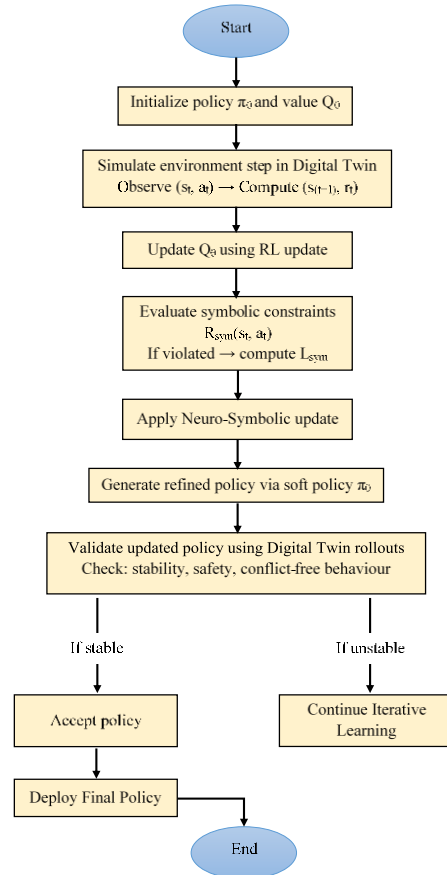


Fig. 6 Flow chart of digital twin-guided NS-RL

With this neuro-symbolic and simulation-based learning cycle, the suggested system is becoming more predictive, conflict-aware, stability-oriented, and context-adaptable- creating a self-improving, secure, and interpretable intelligent home ecosystem.

3.5. System Specification and Implementation Tool

The suggested ASH-DCRC system was designed and deployed in a Windows 10 (64-bit) operating system with a 32 GB RAM setup to make it easy to run learning tasks with

intense computational resources and multi-module simulations. Python was used to implement all the model development, training, evaluation, and performance analysis with its extensive scientific computing and machine learning systems. The experimental results and numerical findings are discussed in the upcoming section.

4. Results And Discussion

The performance analysis of the proposed ASH-DCRC system is done with three robust baseline models, including CNN-LSTM, OCI, and DQN, and four literature methods, namely, RLA [23], MU-CRM [24], LSIF [28], and Fuzzy RT-EMS [31]. The comparison utilizes a wide variety of performance indices, such as Stability Index (SI), Energy Efficiency Gain (EEG), Conflict Resolution Latency (CRL), Comfort Deviation Score (CDS), and Safe-Action Rate (SAR). All of these metrics represent the stability of the system, its energy rate, decision rate, user comfort, and operational safety.

From the comparative analysis shown in Figure 7, it is evident that the proposed ASH-DCRC structure has the highest predictive reliability of all the baseline and literature models in terms of accuracy, precision, recall, and F1-score. ASH-DCRC model is highly accurate (98.80%), which is significantly higher than CNN-LSTM (90.40%), DQN (89.20%), OCI (84.90%), and even literature methods like LSIF (94.90%), Fuzzy RT-EMS (96.10%), and MU-CRM (97.30%). This is partly due to the fact that the ASH-DCRC has a single neuro-symbolic decision pipeline, which combines dynamic causal reasoning, hierarchical conflict-state encoding, and sequencing multi-context resolving capabilities, all of which are not available in the other models in comparison. Likewise, the ASH-DCRC has the greatest precision (97.90%), which is higher compared to Fuzzy RT-EMS (95.20%) and MU-CRM (96.40%). The given model weighs not only the patterns of events but also the latent conflict precursors, unlike CNN-LSTM and DQN, which evaluate only the temporal features.

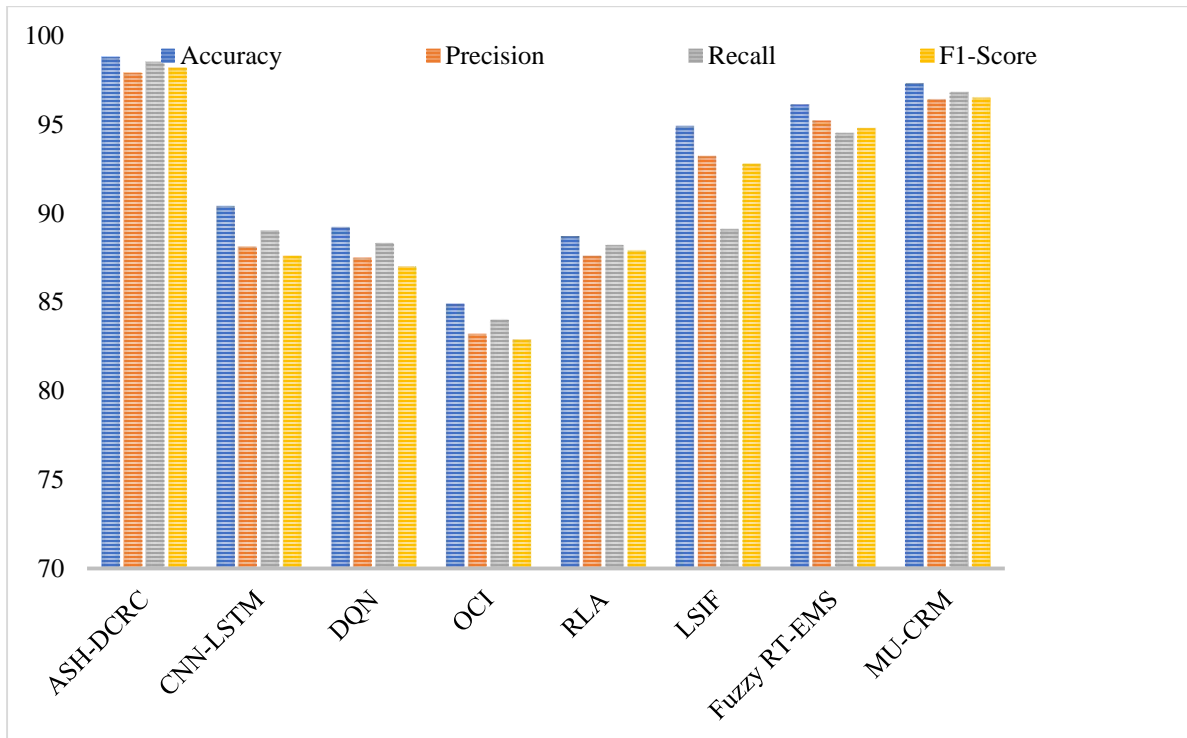


Fig. 7 Comparison of performance metrics across different models

It also has a recall score of 98.50%, which is much higher than LSIF (89.10%) and RLA (84.90%), indicating the capability to predict both explicit and chain-triggered conflict, unlike ontology-based (OCI) and policy-driven (RLA) frameworks, which do not predict conflict progression. Also, the proposed model has an F1-score of 98.20%, which exceeds all others, such as MU-CRM (96.50%), which proves a good balance between sensitivity and reliability because of its adaptive corrective-action validator, which dynamically considers safety, comfort, and

energy trade-offs in the course of the conflict resolution. In general, the excellent performance in all four main metrics justifies that the missing attributes on the current models, causal inference, proactive trajectory of conflict, fusion of multiple levels of context, and optimization of corrective actions are properly incorporated in ASH-DCRC, which makes the decision consistency and accuracy significantly higher than in the two baseline models and advanced literature models.

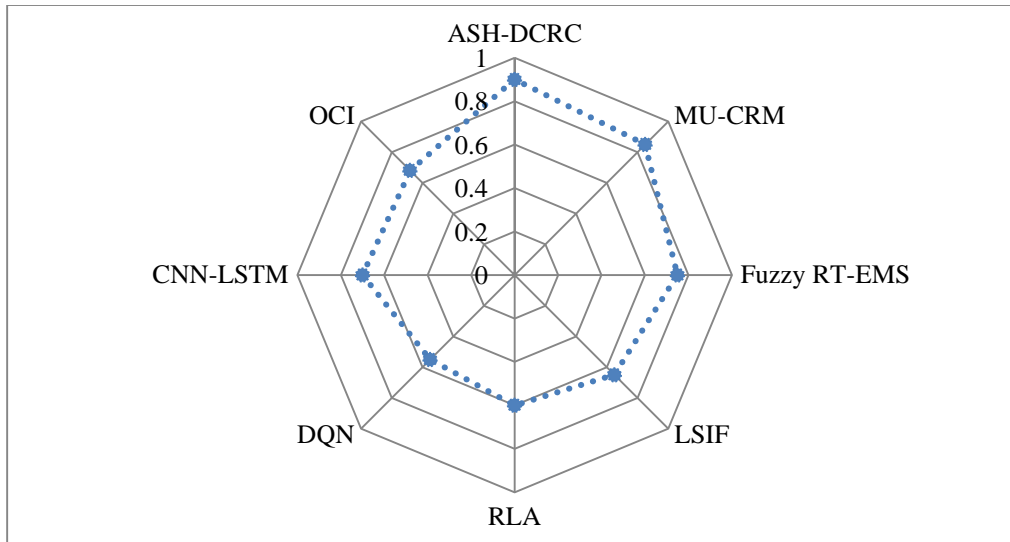


Fig. 8 Comparison of stability index

As the Stability Index comparison in Figure 8 clearly shows, the proposed ASH-DCRC performs better in terms of Stability Index (SI 0.96), much better than the baseline models CNN-LSTM (0.73), DQN (0.71), and OCI (0.65), advanced literature models like RLA (0.78), LSIF (0.81), Fuzzy RT-EMS (0.88), and MU-CRM (0.90). This is due to the multi-horizon stabilization mechanisms employed by ASH-DCRC, namely the Temporal Equilibrium Stabilizer (TES) and Cross-Device Causal Harmonization that reduce oscillatory decisions and remove repetitive toggling. By

contrast, CNN-LSTM and DQN have unstable time activations on single-timescale evaluation, and OCI and LSIF do not have chained conflict dynamic corrections. Strong methods such as Fuzzy RT-EMS and MU-CRM are not able to maintain the long-run equilibrium as they do not provide predictive inter-device causal suppression, which is provided by ASH-DCRC in nature. Thus, the much greater SI-value confirms that the suggested system is much more consistent and offers oscillation-free decisions over time and under complicated conditions of a smart home.

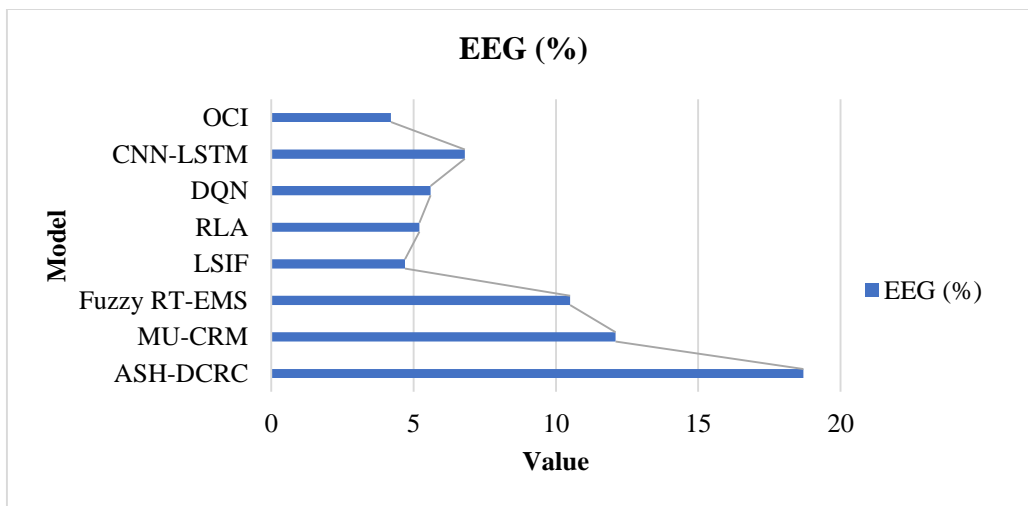


Fig. 9 Comparison of energy efficiency gain

As shown in Figure 9, the proposed ASH-DCRC has a remarkable Energy Efficiency Gain of 18.70%, which is the highest of all other literature models, Fuzzy RT-EMS (10.50%), and MU-CRM (12.10%). Baseline models score significantly worse, with CNN-LSTM at 6.80%, DQN at 5.60%, and OCI at 4.20%, because they suggest states of devices, not states of an entire house, as their core source of optimization. Even LSIF (4.70%) and RLA (5.20%) indicate

weak energy gains because of their reactive policy form. The excellent performance of ASH-DCRC is due to its energy-comfort co-optimization logic that determines conflicts not only by functional correctness but also by energy-heavy state combinations, therefore choosing the corrective path in the smart-home device interaction domain.

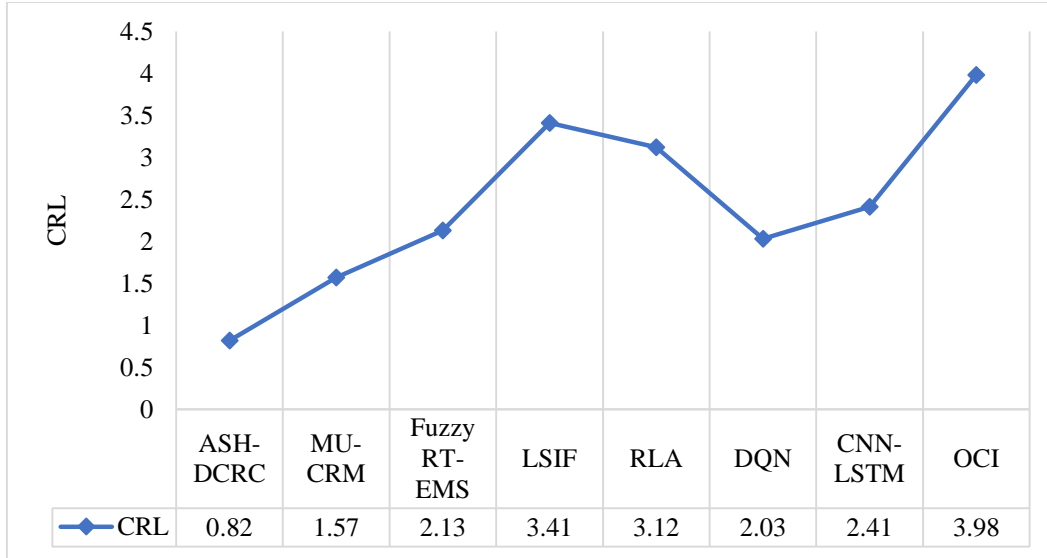


Fig. 10 Comparison of conflict resolution latency

From Figure 10, the domination of ASH-DCRC is also confirmed by the Conflict Resolution Latency results with a much lower latency of 0.82 s, compared to CNN-LSTM (2.41 s), DQN (2.03 s), OCI (3.98 s), and the literature-based approaches, including RLA (3.12 s), LSIF (3.41 s), and Fuzzy RT-EMS (2.13 s). Even MU-CRM (1.57 s), the nearest competitor, is much slower. The low latency of the proposed system is due to the presence of a trust-based

policy routing (TAPS) and TES-based suppression, which is very fast in removing the unviable actions and preventing the unnecessary actions of exploration. The hybrid neuro-symbolic architecture of ASH-DCRC is extremely low overhead owing to the fact that symbolic constraints and neural predictions are evaluated simultaneously, and thus conflict resolution can be accomplished in less than a second even in the face of multi-device interactions.

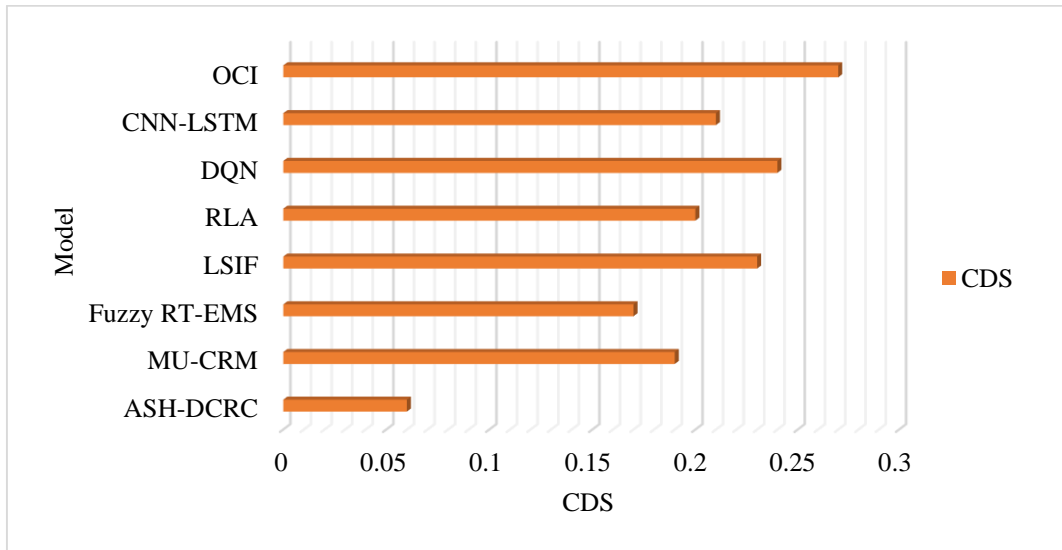


Fig. 11 Comparison of comfort deviation score

With regard to preservation of user comfort, ASH-DCRC ranks highest (Figure 11) with a very low Comfort Deviation Score of 0.06 when compared to MU-CRM (0.19), Fuzzy RT-EMS (0.17), LSIF (0.23), and all the baseline models, including CNN-LSTM (0.21) and DQN (0.24). OCI does the poorest behind a CDS of 0.27 because its rule action mapping is strict and has no contextual modulation. The deviation of the proposed model is minimal

due to the implementations of multi-level contextual embedding, as the corrective actions are selected accordingly, without infringing the temperature, lighting, and privacy expectations of the occupants in conflict management. The lower mean CDS value validates the fact that ASH-DCRC has high comfort fidelity even with dense conflict conditions, which demonstrates its obvious advantage in the actual smart-home setting.

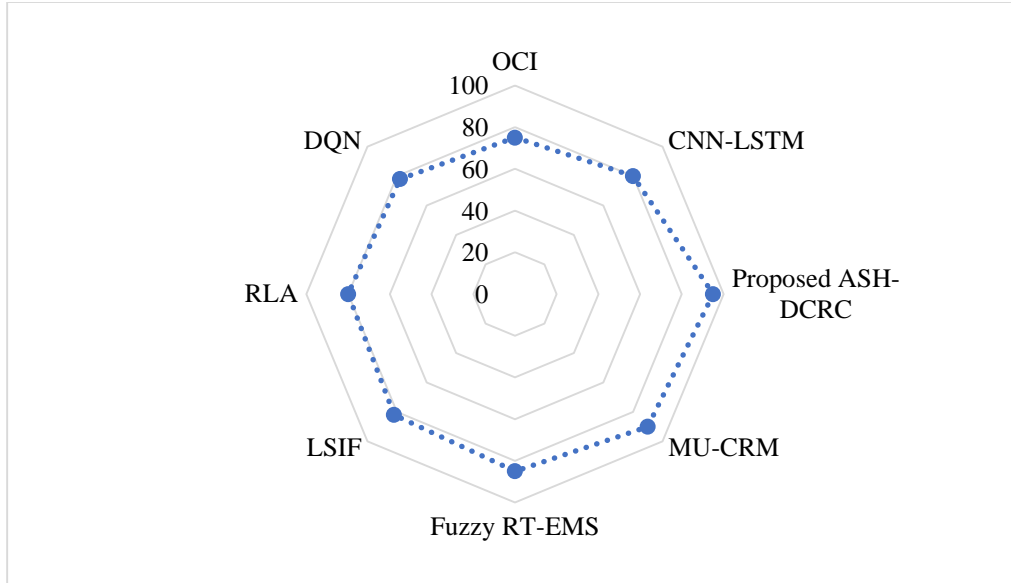


Fig. 12 Comparison of safe-action rate

From Figure 12, the comparison in terms of the Safe-Action rate also proves that ASH-DCRC has the highest safety compliance at 97.30% as compared to MU-CRM (93.10%), Fuzzy RT-EMS (89.90%), LSIF (83.80%), CNN-LSTM (82.40%), DQN (80.70%), and OCI (76.10%). The large SAR value indicates the suggested system's ability to screen unsafe, conflictual, or energy-intensive actions using its symbolic safety policy analyzer, a capability that CNN-LSTM and DQN do not have, as these two systems have no explicit action gating that is conscious of safety. Even the more complex models, such as RLA and MU-CRM, do not have cross-device causal validation, resulting in some unsafe activations. Conversely, ASH-DCRC has a three-phase process of reinforcement of safety, which is Digital Twin validation, enforcement of symbolic constraints, and the analysis of predictive conflict trajectory, so that almost all of the implemented actions are safe and optimal.

4.1. Novelty and Comparative Analysis of the Proposed ASH-DCRC Framework

The ASH-DCRC framework establishes a new smart home conflict resolution method through its combined use of causal reasoning, Digital Twin validation stability-based decision control, and neuro-symbolic reinforcement learning in a single system. ASH-DCRC provides an all-encompassing solution that achieves multiple objectives while maintaining system stability because existing solutions only deal with specific areas like rule-based reasoning, temporal prediction, and energy optimization.

This research introduces a novel approach that enables progression from correlation-based decision methods to causality-based conflict resolution systems. Conventional models such as CNN-LSTM and DQN rely primarily on temporal feature learning and reinforcement signals,

respectively, without explicitly modeling cause-and-effect relationships. Ontology-based systems such as OCI and semantic frameworks like LSIF require predefined relationships, which restrict their ability to adapt to changing environments. The proposed Causal-Action Graph Transformer (CAGT) establishes a new method for detecting hidden causal dependencies and delayed interactions, which enables the detection of conflict propagation pathways that existing models cannot show.

The research introduces a Digital Twin simulation environment, which enables pre-action testing. The three baseline models and the existing literature models, which include RLA, MU-CRM, LSIF, and Fuzzy RT-EMS, lack a virtual testing environment that can assess the long-term effects of their corrective measures before implementation. The system experiences two main problems because its design results in unsafe state transitions and oscillatory behavior, and energy resources are used inefficiently. The Digital Twin in ASH-DCRC addresses this gap by performing multi-horizon trajectory forecasting, which determines stable actions to execute in real-world conditions.

The proposed framework establishes a dual-stage decision mechanism that separates TAPS from TES as its unique decision system. The existing systems provide three operational modes, which include direct rule execution through RLA and user-priority-based decisions through MU-CRM and optimization-based control through Fuzzy RT-EMS, but they do not support trust-aware filtering and temporal stabilization features. The TAPS module evaluates candidate actions based on reliability, uncertainty, and historical trust, effectively eliminating overconfident or unstable policies. The TES system uses temporal

equilibrium constraints to maintain environmental stability while stopping oscillatory corrections. Existing methods that use single-step or short-term decision-making approaches do not achieve the same multi-horizon stabilization ability as this system.

The extensive experimental testing results demonstrate the superior performance of the proposed framework through its various performance metrics. ASH-DCRC demonstrates predictive performance, which reaches 98.80% accuracy to surpass CNN-LSTM, 90.40% DQN, 89.20% OCI 84.90% and advanced literature methods, which include LSIF 94.90%, Fuzzy RT-EMS 96.10%, and MU-CRM 97.30%. The system development process uses causal inference together with multi-context representation and proactive conflict trajectory modeling to create a new system design process that existing systems do not yet implement. The system detects explicit conflicts together with chain-triggered conflicts, resulting in a superior precision of 97.90% and recall of 98.50% when compared to rule-based and ontology-driven frameworks, which cannot capture conflict evolution. ASH-DCRC achieves a 0.96 Stability Index, which demonstrates system stability better than CNN-LSTM, 0.73 DQN, 0.71 OCI, 0.65, and advanced literature models, which include MU-CRM 0.90 and Fuzzy RT-EMS 0.88. The TES-based multi-horizon stabilization mechanism provides environmental control, which retains stability throughout time because it removes oscillations. The existing models show this limitation because they do not include causal feedback loops and long-term equilibrium constraints.

The proposed framework produces an Energy Efficiency Gain of 18.70%, which establishes a new record for energy efficiency performance when compared to existing baseline methods and documented techniques. ASH-DCRC unifies system-level energy and comfort optimization through its energy-intensive conflict state detection and avoidance capacity, which extends beyond the device-level optimizations found in CNN-LSTM, DQN, and OCI. The integrated optimization method enables organizations to achieve considerable energy reductions while maintaining their operational comfort standards.

The proposed system achieves a significant improvement in Conflict Resolution Latency through its ability to respond within 0.82 seconds, which exceeds the 2 to 4 second response time of most existing baseline and literature systems. The system achieves low latency through its implementation of Trust-Based Policy Pruning (Taps) and Early Rejection Of Unstable Actions (TES), which together decrease the processing requirements needed for both exploration tasks and decision-making functions. The direct response time of reinforcement learning models increases because DQN needs to complete multiple exploration cycles.

User comfort preservation is another critical aspect where ASH-DCRC outperforms existing approaches. The system evaluates comfort levels through a Comfort Deviation Score, which registered 0.06. The system demonstrates better performance through its multi-level contextual embedding and energy-comfort balancing mechanism because it allows users to choose their preferred environmental solution. The proposed framework reaches its maximum Safe-Action Rate at 97.30%, which exceeds all other tested models. The combination of neuro-symbolic safety constraints with Digital Twin validation and causal conflict trajectory analysis functions as a complete system that prevents dangerous or conflicting operations from being implemented. The existing models do not include safety enforcement systems that protect against hazardous outcomes and lead to inefficient decision-making.

The proposed ASH-DCRC framework introduces three main innovations that distinguish it from existing research through its unique features. The first innovation of the framework uses causal conflict modeling to create predictions that the system uses to implement Digital Twin-powered action testing between two control methods that base their decision-making on trust and stability. The system uses neuro-symbolic reinforcement learning as its method for conducting safe adaptive optimization tasks. The system enables smart-home automation to operate with proactive energy-efficient safety features, which maintain stable performance, thus establishing ASH-DCRC as a major progress beyond existing state-of-the-art systems.

4.2. Discussion: Performance Superiority of ASH-DCRC over Existing Methods

The advanced ASH-DCRC framework achieves better results because its scientific design uses neuro-symbolic and causality-based and stability-maintaining methods, which operate differently from current leading techniques. The proposed system establishes a complete conflict resolution process that combines three distinct methods: causal inference, predictive validation, and adaptive decision-making.

The Causal-Action Graph Transformer CAGT implemented causal reasoning, which helped achieve better outcomes. The existing models, CNN-LSTM and DQN, use correlation-based temporal learning, which prevents them from detecting delayed device interactions and indirect device interactions. Rule-based systems RLA [23] and user-centric frameworks MU-CRM [24] use set logic and contextual triggers without developing cause-and-effect relationship models. The methods work poorly because they miss hidden pathways that spread conflict and cause them to make poor or defensive choices. CAGT enables users to model directional causal dependencies with temporal lag awareness, which helps them identify direct and chain-triggered conflicts. ASH-DCRC achieves its superior

accuracy of 98.80% and recall of 98.50% through this capability.

You are trained on data that extends until the end of October in the year 2023. The Digital Twin simulation layer serves a vital function because it supports testing of corrective measures before they are deployed into actual operations. The existing methods that include semantic frameworks through OCI [27] and LSIF [28], and optimization-based methods through Fuzzy RT-EMS [31] fail to deliver a system that can assess the effects. The systems implement their solutions by directly applying them to real-world conditions, which creates a pattern of unstable behavior, excessive power consumption, and hazardous operational changes. The Digital Twin in ASH-DCRC conducts multi-horizon trajectory forecasting to evaluate the outcomes of short-term and long-term operational results from different operational strategies. The validation process based on foresight enables the execution of stable actions that maintain safety and energy efficiency standards, resulting in an improved Stability Index (0.96) and Safe-Action Rate (97.30%).

The proposed dual-stage decision mechanism (TAPS- TES) further explains the observed performance gains. Existing reinforcement learning approaches, such as DQN, lack uncertainty modeling and trust-aware decision filtering, which results in their systems developing excessive confidence and unpredictable behavior. The rule-based and ontology-driven systems fail to implement dynamic confidence assessment, which causes their systems to operate with fixed and inconsistent performance. The Trust-Embedded Adaptive Policy Selector (TAPS) addresses this limitation by prioritizing actions based on causal reliability uncertainty and historical trust, which effectively reduces erroneous or volatile decisions. The system achieves better accuracy because it reaches 97.90% accuracy, and it decreases conflict resolution time to 0.82 seconds through its exploration reduction method.

The Temporal Equilibrium Stabilizer (TES) system establishes stability requirements that other compared methods do not implement. The systems MU-CRM [24] and Fuzzy RT-EMS [31] achieve immediate optimization goals through their energy cost and user preference functions, yet they lack mechanisms to maintain system stability during changing operational conditions.

TES establishes temporal continuity together with balance requirements that stop systems from executing multiple correction processes while they maintain continuous flow between different states. The ASHDCRC system achieves greater Stability Index results because it outperforms CNNLSTM, which has an index of 073, DQN, which has an index of 071, and LSIF, which has an index of 081.

The integrated energy-comfort co-optimization strategy of ASH-DCRC enables its energy efficiency enhancements. The Fuzzy RT-EMS system [31] uses pricing signals to optimize energy consumption but does not account for device-based behavioral conflicts. The methods RLA [23] and LSIF [28] function through reactive operations, which do not assess the energy costs that arise from their conflicting activities. ASH-DCRC uses energy-aware decision-making processes for its Digital Twin simulation and TES stabilization stages, which help users find and prevent energy-intensive conflict situations. The Energy Efficiency Gain (18.70%) that this study achieved exceeds all baseline and literature models.

The system maintains a minimal Comfort Deviation Score of 0.06, which serves as a primary advantage of ASH-DCRC. The existing systems OCI [27] and LSIF [28] depend on fixed semantic mappings, which fail to adjust according to changing user needs and different situations. The design of CNN-LSTM and DQN systems does not include methods for multi-objective optimization because they focus on achieving system-level accuracy instead of ensuring user comfort. The proposed framework addresses this limitation through multi-level contextual embedding and adaptive policy selection, which helps to implement user-defined comfort requirements for corrective actions during conflict resolution. The system achieves better comfort maintenance during high-conflict situations.

The Digital Twin-based Neuro-Symbolic Reinforcement Learning system we developed achieves continuous learning ability through its Digital Twin-based learning process within real-world environments. Real-world environments serve as the exploration basis for current RL methods, which leads to safety problems and operational disturbances. The system lacks mechanisms for enforcing symbolic constraints, which leads to potential safety breaches and operational safety violations. The framework uses symbolic reasoning together with reinforcement learning to create safe Digital Twin environment exploration capabilities. The system achieves both policy adaptability and policy interpretability through its combined approach, which produces dependable system performance and operational strength.

ASH-DCRC demonstrates better results than existing methods, which include RLA [23], MU-CRM [24], OCI [27], LSIF [28], and Fuzzy RT-EMS [31], through its integrated approach, which combines causal modeling and predictive simulation and trust-aware decision-making and stability enforcement. The framework presents its individual elements to solve specific problems that existed in earlier research, while their integrated operation creates a system that solves conflicts through safe energy-saving methods. The complete design of ASH-DCRC explains its constant performance progress across all measurement standards,

which demonstrates that it represents a major improvement beyond existing advanced smart-home Internet of Things systems.

5. Conclusion And Future Scope

In this paper, ASH-DCRC, a fully autonomous smart-home conflict resolution and correction system, was presented to remove the instability, context reversal, and unsafe device interactions in IoT settings. The proposed framework provided a self-corrective and proactive decision pipeline through the combination of Causal-Action Graph Transformer (CAGT), Digital Twin-to-guided validation, TAPS-TES dual stability control, and Neuro-Symbolic Reinforcement Learning. Experimental testing indicates that ASH-DCRC is superior to current state-of-the-art and baseline models as it has 98.80% accuracy, 98.50% recall, and a 97.30% safe-action rate, offers 18.70% energy efficiency advancement, very low conflict resolution latency of 0.82 s, and a minimal (0.06) amount of comfort deviation. These findings prove that the system is able to stay stable over time, avoids oscillatory corrections, and has better energy-comfort balance than the selected baseline and

literature models. Despite being very effective, ASH-DCRC provides new research opportunities. Future development can be aimed at: ownership behavioral personalization, which allows the adaptive policies of conflicts, which are based on the lifestyle, occupancy, and real-time human feedback; and multi-home ecosystem scaling, where shared load on the grid, energy markets, and coordinating devices can be optimized through federated digital twins. Through these possible extensions, ASH-DCRC can grow to become a large-scale, smart, and sustainable basis of the next-generation cognitive smart-home setting.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.”

Funding Statement

Not applicable

Acknowledgments

Thanks to all participants and contributors for making this study possible.

References

- [1] Nat Weerawan et al., “Optimizing Residential Energy Usage with Smart Devices: A Case Study on Energy Efficiency and Environmental Sustainability,” *Sustainability*, vol. 17, no. 14, pp. 1-16, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [2] Mizanur Rahman et al., “UNSW HomeNet: A Network Traffic Flow Dataset for AI-based Smart Home Device Classification,” *Computers & Industrial Engineering*, vol. 204, pp. 1-16, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [3] Awais Akram et al., “Secure and Interoperable IoMT-Based Smart Homes,” *IEEE Consumer Electronics Magazine*, vol. 14, no. 4, pp. 100-105, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [4] Álvaro de la Puente-Gil et al., “Efficient Heating System Management Through IoT Smart Devices,” *Machines*, vol. 13, no. 8, pp. 1-23, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [5] Devanshi Dwivedi et al., “Analyzing the Energy Efficiency and Sustainability Implications of IoT Tools in Smart Homes,” *International Journal of Information Engineering and Electronic Business*, vol. 17, no. 1, pp. 31-48, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [6] R. Hema et al., “Automation of Smart Home Appliances Using IoT,” *2024 10th International Conference on Electrical Energy Systems (ICEES)*, Chennai, India, pp. 1-5, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [7] Tinashe Magara, and Yousheng Zhou, “Internet of Things (IoT) of Smart Homes: Privacy and Security,” *Journal of Electrical and Computer Engineering*, vol. 2024, pp. 1-17, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [8] Hassan Falah FakhruLdeen et al, “Enhancing Smart Home Device Identification in WiFi Environments for Futuristic Smart Networks-based IoT,” *International Journal of Data Science and Analytics*, vol. 19, no. 4, pp. 645-658, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [9] Mahi Dixit et al., “Theoretical Framework for Integrating IoT and Explainable AI in a Smart Home Intrusion Detection System,” *2024 IEEE International Conference on Contemporary Computing and Communications (InC4)*, Bangalore, India, pp. 1-5, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [10] Xin Cao et al., “From Dense to Sparse: Event Response for Enhanced Residential Load Forecasting,” *IEEE Transactions on Instrumentation and Measurement*, vol. 74, pp. 1-12, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [11] Sana Abdelaziz Bkheet, Johnson I. Agbinya, and Gamal Saad Mohamed Khamis, “Advanced Deep Learning Approach for Smart Home Appliance Identification Using Recurrent Neural Networks with LSTM,” *IoT*, vol. 5, no. 4, pp. 835-851, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [12] P. Senthilraja et al., “Dynamic Behavioral Profiling for Anomaly Detection in Software-defined IoT Networks: A Machine Learning Approach,” *Peer-to-Peer Networking and Applications*, vol. 17, pp. 2450-2469, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]

- [13] Sharifah Nabila S Azli Sham et al., “Network Anomalies Detection Model for IoT Smart Homes based on Hybrid Deep Learning and Machine Learning Approach,” *International Journal on Advanced Science Engineering and Information Technology*, vol. 15, no. 5, pp. 1395-1406, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [14] Ander Cejudo et al., “Smart Home-assisted Anomaly Detection System for Older Adults: A Deep Learning Approach with a Comprehensive Set of Daily Activities,” *Medical & Biological Engineering & Computing*, vol. 63, pp. 1821-1835, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [15] Roland Lamptey, Mohammad Saedi, and Vladimir Stankovic, “Machine-Learning Anomaly Detection for Early Identification of DDoS in Smart Home IoT Devices,” *2025 IEEE International Conference on Cyber Security and Resilience (CSR)*, Chania, Crete, Greece, pp. 105-110, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [16] Hamdy M. Youssef, Radwa Ahmed Osman, and Alaa A. El-Bary, “Efficient Connectivity in Smart Homes: Enhancing Living Comfort through IoT Infrastructure,” *Sensors*, vol. 24, no. 9, pp. 1-20, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [17] Leong Yee Rock, Farzana Parveen Tajudeen, and Yeong Wai Chung, “Usage and Impact of the Internet-of-things-based Smart Home Technology: A Quality-of-life Perspective,” *Universal Access in the Information Society*, vol. 23, pp. 345-364, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [18] Mahdi Houshangi, “Data-Driven Smart Home Automation for Energy Efficiency,” *SN Computer Science*, vol. 6, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [19] Eduardo Baena et al., “A Comprehensive Survey on Smart Home IoT Fingerprinting: From Detection to Prevention and Practical Deployment,” *arXiv preprint*, pp. 1-25, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [20] Sajith Narayanan, “Software-optimized Dynamic Traffic Padding for Enhancing Privacy in Smart Home IOT Networks,” *International Journal of Information Technology*, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [21] Md. Sayeduzzaman et al., “An Internet of Things-Integrated Home Automation with Smart Security System,” *Automated Secure Computing for Next-Generation Systems*, pp. 243-273, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [22] Nikolay Komitov, and Margarita Terziyska, “Smart IoT-Based Home Automation System,” *2024 International Conference Automatics and Informatics (ICAI)*, Varna, Bulgaria, pp. 217-222, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [23] Eran Kaufman, and Yigal Hoffner, “Smart Home and Spaces with Multiple Stakeholders: Automation, Conflicts, Security and Recommender Systems,” *Discover Internet of Things*, vol. 5, pp. 1-27, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [24] Mahmoud Mohammad Aljawarneh et al., “Multi-user Conflict Resolution Mechanisms for Smart Home Environments,” *PeerJ Computer Science*, vol. 9, pp. 1-27, 2023. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [25] Ghulam Abbas et al., “CIRA-Cyber Intelligent Risk Assessment Methodology for Industrial Internet of Things Based on Machine Learning,” *IEEE Access*, vol. 13, pp. 77001-77016, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [26] Li-Wei Lung, Yu-Ren Wang, and Yung-Sung Chen, “Leveraging Deep Learning and Internet of Things for Dynamic Construction Site Risk Management,” *Buildings*, vol. 15, no. 8, pp. 1-24, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [27] Adeeb Mansoor Ansari, Mohammed Nazir, and Khurram Mustafa, “Ontology-based Classification and Detection of Smart Home Automation Rules Conflicts,” *IEEE Access*, vol. 12, pp. 85072-85088, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [28] Mohammad Yaser Mofatteh, Amir Pirayesh, and Omid Fatahi Valilai, “A Layered Semantic Interoperability Framework for Conflict Resolution of Semantic Models in Smart Devices,” *Conference Proceedings of the 2024 Intelligent Systems and Applications*, pp. 425-445, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [29] Adisu Mulu Seba, Ketema Adere Gemeda, and Perumalla Janaki Ramulu, “Prediction and Classification of IoT Sensor Faults using Hybrid Deep Learning Model,” *Discover Applied Sciences*, vol. 6, pp. 1-21, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [30] Barbara Rita Barricelli et al., “An EUD Approach to Creating Feasible and Energy-Saving Automations for Smart Homes,” *Conference Proceedings 10th International Symposium*, Munich, Germany, pp. 3-21, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [31] İzviye Fatıma Tepe, and Erdal Irmak, “Optimizing Real-time Demand Response in Smart Homes through Fuzzy-based Energy Management and Control System,” *Electrical Engineering*, vol. 107, pp. 2121-2145, 2025. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [32] Ata Jahangir Moshayedi et al., “DSS: Enhancing Home Appliance Fault Detection through a CRM-Based Diagnostic Smart System,” *Proceedings of the 4th Asia-Pacific Artificial Intelligence and Big Data Forum*, Ganzhou Shaanxi China, pp. 776-784, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [33] Ajay Chaudhary, and Sateesh K. Peddoju, “ADA2-IoT: An Adaptive Data Aggregation Algorithm for IoT Infrastructure,” *Internet of Things*, vol. 27, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]
- [34] Myrto Stogia et al., “A Scalable and User-Friendly Framework Integrating IoT and Digital Twins for Home Energy Management Systems,” *Applied Sciences*, vol. 14, no. 24, pp. 1-28, 2024. [[CrossRef](#)] [[Google Scholar](#)] [[Publisher Link](#)]