Data Driven Stochastic Game Network-Based Smart Home Monitoring System Using IoT-Enabled Edge Computing Environments

Prabal Verma, *Member, IEEE*, Sandeep K. Sood, Harkiran Kaur, Mohit Kumar, Huaming Wu, *Senior Member, IEEE*, and Sukhpal Singh Gill

Abstract—Edge computing plays a crucial role in the processing of Consumer Internet of Things (IoT)-enabled latency-sensitive applications. In smart homes, dynamic action strategies based on multiple IoT objects with edge processing can be the best solution for handling adverse events. To overcome these challenges, the use of Stochastic Game Net (SGN) forming IoT devices as players with predefined action sets is one of the feasible solutions. Relative to this context, the edge-assisted IoT-enabled data-driven SGN model is proposed to handle various events in the smart home environment. Stochastic Petri Nets (SPNs) and game theory are integrated into our proposed model to build data-driven dynamic SGNs for the smart home environment. Dynamic SGNs for a comprehensive smart home system are generated in real-time through transitions based on sensor data, enhancing interoperability and scalability in smart home environments. We use the Net logo tool and state-of-the-art smart home sensor datasets to generate dynamic SGNs for various events. Experimental results demonstrate the effectiveness of the proposed model within a data-driven smart home environment. It shows that the present work significantly outperforms other state-of-the-art techniques in terms of decision-making at the edge layer. Moreover, using the proposed system the energy efficacy increased to around 39mJ/K nodes, and the average temporal delay for different events was reduced significantly.

Index Terms—Edge computing, stochastic game net, game theory, consumer IoT, data-driven modeling.

Prabal Verma is with the Department of Information Technology, National Institute of Technology at Srinagar, Srinagar 190006, India (e-mail: prabalverma357@gmail.com).

Sandeep K. Sood is with the Department of Computer Applications, National Institute of Technology Kurukshetra, Kurukshetra 136119, India (e-mail: san1198@gmail.com).

Harkiran Kaur is with the Department of Computer Science, Guru Nanak Dev University, Amritsar 143005, India (e-mail: harkiran1992@gmail.com).

Mohit Kumar is with the Department of Information Technology, National Institute of Technology at Jalandhar, Jalandhar 144011, India (e-mail: kumarmohit@nitj.ac.in).

Huaming Wu is with the Center for Applied Mathematics, Tianjin University, Tianjin 300072, China (e-mail: whming@tju.edu.cn).

Sukhpal Singh Gill is with the School of Electronic Engineering and Computer Science, Queen Mary University of London, E1 4NS London, U.K. (e-mail: s.s.gill@qmul.ac.uk).

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I. INTRODUCTION

INTERNET of Things (IoT) is a prominent term that touches every aspect of our lives and provides insights into the status of various objects and systems [1]. Consumer IoT represents the linkage of intelligent consumer electronics or entities to the Internet, enabling them to perceive their surroundings, generate insights, and communicate effectively with both humans and other digital devices [2]. Many smart applications in consumer electronics like healthcare or Internet of Medical Things (IoMT) [3], [4], autonomous vehicles assisted by high-speed mobile networks [5], environment monitoring [6], big data recommendation [7] and building smart cities, are based on common technologies such as IoT, Federated Reinforcement Learning [8] and Digital Twins [9]. For instance, the integration of IoT in smart home monitoring has significantly transformed the way homes are managed and monitored, which involves connecting various electronic devices and sensors to a network, enabling them to communicate and share data. This interconnection allows for seamless automation, monitoring, and control of various aspects within the home [10]. Smart home monitoring systems leverage IoT to collect data from sensors, e.g., motion detectors, cameras, temperature sensors, and door/window sensors, creating a comprehensive view of the home environment [11]. Moreover, incorporating game-theoretical decision-making with IoT-assisted electronic technology in smart homes provides solutions related to effective event management and minimizing loss to the maximum extent.

A. Edge Computing in Smart Homes

Generally, IoT-based data-driven applications require real-time decision-making and actions. Edge computing, also known as Mobile Edge Computing (MEC) or Multi-Access Edge Computing, is a distributed architecture that brings processing and storage resources for applications in proximity to the place of generation or consumption of data [12], [13]. By keeping the computational capacity close to the users, devices, or data sources, edge computing delivers benefits such as low latency, high bandwidth, device processing, and data offloading, improving the performance, security, operating cost, and reliability of applications and services [14], [15]. Edge computing revolutionizes smart home monitoring by enabling real-time data processing at the source, on electronic

edge devices, or nearby servers. This approach reduces latency, ensuring immediate responses to security incidents or emergencies. Edge computing optimizes bandwidth usage, as only relevant, secure or pre-processed data is transmitted to the cloud layer, enhancing efficiency [16] and preserving privacy [17].

B. Motivation and Our Contributions

Game theory provides vast solutions in the form of decision-making services to various problems in smart home environments. However, utilizing automated capabilities of conventional game theory with IoT frameworks is a tough task due to the lack of modeling features to model data-driven complex interactions and mixed strategies by IoT-based electronic devices [18]. Secondly, dynamic or unrelated scenarios in consumer electronic-centric IoT systems are difficult to map or update mathematical using game theory. Thirdly, assigning preferences to players is complex in a game theory environment. Lastly, in consumer electronics, nodes forming IoT applications, their actions can't be prioritized using game theory, which leads to difficulty in quantifying the cost for actions. Conspicuously, this research incorporates both game theory and stochastic Petri nets (SPN), called stochastic game nets (SGN). Finally, decision-making in smart homes based on data-driven SGN has several benefits as follows:

- SGN can represent an effective data-driven dynamic sensor displacement model for efficient analysis of various events in smart homes.
- SGN can access the smart home consumer electronic sensor environment as an *n*-player game model.
- SGN also effectively maps different events, strategies, IoT-driven integration, and game equilibrium.
- SGN takes automated decisions based on numerous smart home-oriented adverse event attributes collected from consumer electronics.

Motivated by the SGN capabilities, this research presents an efficient data-driven edge computing-based SGN smart home monitoring system. The current research focuses on the following major objectives.

- Developing data-driven smart home environments using *n*-player game theory, where every consumer-centric IoT device within the house operates as an independent player with associated payoffs for each action undertaken.
- Temporal analysis of IoT-driven data using SGN edge model and automated decision making.
- Formulating an effective mathematical formalization for SGN-based smart homes and analyzing the model with the large sensor test beds.
- The proposed edge-assisted data-driven SGN smart home model is validated using execution delay, energy consumption, and comparative analysis with state-of-the-art datasets and alert generation statistical results.

The rest of this paper is framed as follows. Section II discusses and analyzes the related works. Section III proposed SGN for an IoT-Edge-based smart home environment. Section IV empirically evaluates the system's performance and engages in a comprehensive discussion. Finally, Section V provides the paper's concluding remarks.

II. RELATED WORK

We have divided the related work into two different categories, namely, game theory in IoT and SPNs in IoT.

A. Game Theory in IoT

The adoption of game-based decision models is on the rise within IoT environments. Game theory consists of analytical tools for making decisions under conditions of uncertainty and interdependence. Ding et al. [19] proposed a differential game model to improve the stability of nodes in an IoT environment. Kumar et al. [20] conducted an assessment of a Bayesian coalition game within an IoT environment, utilizing game theory and learning automata (LA). In this context, the LA serves as the players, each equipped with adjustable learning rates, participating in the coalition game. These players make decisions through competitive learning with variable learning rates, guided by a newly defined utility function. This approach facilitates the rapid attainment of a Nash equilibrium within the game. Kaur and Sood [21] proposed a game-based decision system for the performance evaluation of employees in the smart industry. Zhang et al. [22] conducted a study on the management of IoT service delivery. This study took into account the factors of substitutability, externalities, and complementarity that arise in the delivery of IoT services, influenced by the diverse array of IoT components in mobile systems.

B. Stochastic Petri Net in IoT

Zeng et al. [23] introduced a mathematical tool based on SPNs for assessing and quantifying the dependability of communication networks within smart grids. This approach extends beyond the traditional metrics of reliability and availability, incorporating the analysis of transient and steady-state probabilities. Ping et al. [24] proposed SPN to analyze and design software systems to develop an application software security testing approach rooted in the SPN model. Zhang et al. [25] introduced a real-time production model referred to as the "performance analysis and exception diagnosis model", which incorporates a hierarchical timed-colored Petri net featuring smart tokens. This model is utilized for precise analysis of sensor data to extract accurate information. Sanahmadi et al. [26] introduced a model based on stochastic reward nets (SRN) for modeling and quantitatively assessing system energy consumption. Moreover, to focus more on the novelty perspective, an extensive comparative analysis of the recent works on IoT, game theory, Petri nets, and its applicability in smart city applications were considered focusing on several fields, i.e., objectives, algorithms, and limitations with future work in Table I.

III. SYSTEM MODEL

In this section, we discuss the system model and its components in detail.

TABLE I
COMPARATIVE ANALYSIS OF THE PROPOSED SYSTEM WITH OTHER STATE-OF-THE-ART METHODOLOGIES

Work	Objective	Algorithm/Technique	Limitations and Future work
Ding et al. [19]	To achieve optimal resources and find the selfish nodes and malicious behavior	The Differential Game Model	Proposed work is not tested in a real IoT environment and needs to measure accuracy to evaluate the performance.
Zhang et al. [22]	To improve the price and performance by considering complementarity, externalities, and substitutability	Multi-leader Game-Theoretic Approach	The proposed approach can be applied to complex market behavior and online pricing.
Ping et al. [24]	To enhance the security of software and avoid software failure	Stochastic Petri nets theory	Efficiency and scope of proposed work is limited.
Kaur et al. [27]	To improve integrity, confidentiality, and availability.	Stochastic Petri nets and game theory approach	The proposed work can be used to detect the anomalies in the network with high accuracy.
Sanahmadi et al. [26]	To optimize energy consumption and latency of IoT devices	Stochastic reward net model	The proposed work can be used to enhance other quality attributes of IoT.
Han et al. [28]	To optimize multi-regional integrated energy systems based on cooperative games.	Latin-hypercube sampling, Wasserstein metric, and Nash bargaining game.	Scope is limited to optimization problems with multiple operators.
Ajao and Apeh [29]	To develop a security framework for the smart cities' sustainable edge computing vulnerabilities.	Reinforcement learning, Petri-nets and Genetic Algorithms.	Detection and mitigation of fog computing attacks and cloud computing vulnerability were not covered. Moreover, security challenges of adopting 5G networks over smart cities are also a major concern.
Guo et al. [30]	Autonomous behavioral decision framework for vehicular agents.	Cyber-physical social intelligence, Iterative search algorithm, and Universal optimization algorithm.	Networking and intelligence required in the future for the new energy vehicle industry (decision model for intelligent driving decision system).
Sun et al. [31]	To present a hierarchical framework that coordinates the heterogeneity among tasks and servers to improve resource utilization in a vehicular network.	Bargaining-based increment approach and matching method.	Task processing rate and task processing delay related to other efficient methodologies in vehicular edge networks can be explored.
Bhuyan and Chakraborty [32]	To develop feature selection multiapproach with the classification of diverse datasets.	Extensible particle swarm optimization, global and local searching, feature ranking and clustering, computational cost-based feature selection, and multi-objective optimization.	Different wrapping methods and ensemble learning can be used in the future for testing to fulfill the social problem.
Dehory et al. [33]	To provide a discrete block-chain-based solution for clustered edge intelligence makes the edge devices' events history immutable and easily traceable.	Secured cluster edge intelligence, and blockchain.	Numerous challenges like network overhead, scalability, interoperability, and technical validation based on real implementations for using blockchain with cluster edge intelligence need to be addressed in the future.
This work	To provide event data in real-time for better decision-making, energy efficient modeling and improve interoperability and scalability in smart home	Edge computing, Stochastic Game Networks	In the future, the proposed approach can enhance the cost and be applied to smart indoor applications and security.

A. Sensor Types in Smart Homes

Smart home consists of multiple sensors and smart devices such as door sensors, bed sensors, fire sensors, motion detectors, Global Positioning System (GPS), and fall detection sensors. These sensors are connected to an Edge server located near the smart home. The server handles many responsibilities such as intercommunication of smart devices, and intra-communication with the outside world. The Edge server decides on some action, appropriate request is forwarded to third parties located outside the smart home such as shops, marts, hospitals, grocery stores, and doctors.

B. SGN-Assisted Edge Computing

In smart homes to build real-time applications, IoT is currently associated with the edge computing paradigm to produce effective results. As shown in Fig. 1, the assisted-IoT-enabled SGN model is proposed to handle various events in a smart home environment. Real-time SGN graphs are created on the Edge node to handle various adverse events such as *Fire*, *Theft*, *Patient health severity*, and *Grocery*

exhaust information. Algorithm 1 shows the procedural steps for dynamic SGN creation in smart home applications. Consciously, various events happening can be determined in real-time in the Edge node by adopting SGN and game theory for decision-making. Henceforth, the Edge node will generate real-time responses for various events. These events related to dynamic SGN are created regularly after a particular time interval. If any unappropriated event happens, that event-related SGN will be attached to the current SGN so that a real-time Alert can be generated based on the parameters shown in Table V. In the proposed system, the Edge nodes interact with each other and send a message to generate an alert. In the patient health event, the real-time information of the patient will be given to the responder based on the current information. The caretaker will decide if the patient needs to shift to the hospital or not. If there is a fire in the smart home, the Edge nodes interact with each other and send messages to initiate water, alert the inmates, neighbors, fire services, etc. Moreover, the complete mathematical data-driven SGN generation with a decision-making procedure is carried out in the next subsection.
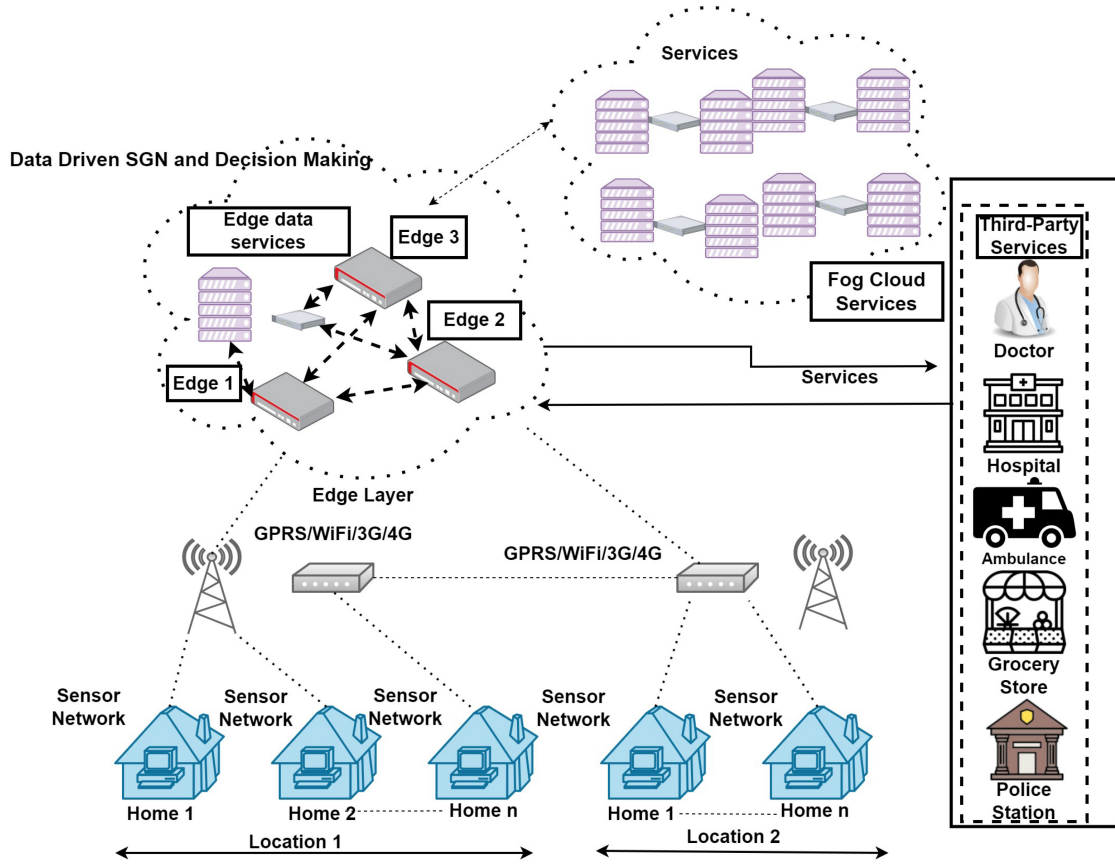
Fig. 1. Proposed abstraction data-driven model for SGN-based smart home connection.

Algorithm 1: Computing SGN Graph for Each Player in Smart Home Environment

Input: N, P, T
Output: R, π

1: Identify the game players and the game type.
2: Construct transition set $\pi \rightarrow [0, 1]$, the probability of selecting a specific transition to move from one state to another within the set of actions. Here, transition set $\pi(T_1^n) + \pi(T_2^n) + \ldots + \pi(T_n^n) = 1$ as per players objectives and action.
3: Assign reward values to each player as R:
   $T \rightarrow (R_1, R_2, R_3, \ldots, R_n)$
4: Construct the place set $P^k = \bigcup_{a \in A^k} p_a^k$ for each player, and SGN based on action results.
5: According to the SGN model of the player, calculate the corresponding Game Equilibrium as
   $R^i(M^{1*}, M^{2*}, \ldots, M^{(i-1)*}, M^{(i*)}, M^{(i+1)*}, \ldots, M^{Q*})$, for any player i, M^i is the alternative strategy and the Game equilibrium strategy is M^{Q*}
6: λ values are assigned for each graph transition for different events.
7: Simplify SGN model and solve the steady-state probability.

C. Stochastic Game Nets in Smart Homes

Definition 1: A smart home environment equipped with numerous sensors can be structured to create an SGN using the following sets of elements:

$$SGN = \{N, A, P, T, F, \pi, R, X, \lambda, I, U\}. \quad (1)$$

The description of SGN elements is outlined below:

- $N = (1, 2, 3, \ldots, n)$ signifies the collection of IoT devices within a smart home. As previously mentioned, these IoT devices serve as game players. Two distinct player types, namely the destructive player and the detective player, are employed in smart homes. Detective players are IoT devices responsible for detecting any critical activities and promptly notifying the administrator. Subsequently, the administrator player takes measures to safeguard the home from the destructive player.

- A represents the assortment of actions that a player can choose from. In cases where a player decides not to take any action, it is symbolized as $\varnothing$. In the smart home, sensors can act as players whenever any action has to be taken based on the trigger of an individual sensor, inputs from other sensors are also taken so that the result of the action is more effective.

- $P = (1, 2, 3, \ldots, s)$ designates the collection of states for game players. The vertices $p \in P$. Players' selections of specific actions induce transitions from one location to another within the system efficiently, where S_i signifies the set of places where the respective IoT device is situated. These IoT devices have the flexibility to undertake any action, denoted as $p \in S$.

- $T = T^1 \cup T^2 \cup \ldots \cup T^n$ is the collective transition set for IoT players. Here, T^k represents the set of transitions associated with player $k \in N$.

- F comprises the input and output arcs linking places with transitions and vice versa. $F \subseteq I \cup O$ is set of arcs, where $I \subseteq I(P \times T)$ and $O \subseteq I(T \times P)$ such that $P \cap T = \Phi$ and $P \cup T\_ = \Phi$, where Φ is empty set.
- $\pi \rightarrow [0, 1]$ represents the probability of selecting a specific transition to move from one state to another within the set of actions. The summation of probabilities for all transitions chosen by a player is denoted as $\pi(T_1^n) + \pi(T_2^n) + \cdots + \pi(T_n^n) = 1$. Here, the values 0 and 1 constitute a routing policy, reflecting the probability of selecting a particular transition. A value of 0 indicates a low likelihood of transitioning, while a value of 1 signifies a high likelihood of transitioning.
- $R: T \rightarrow (s_1, s_2, \ldots, s_n)$ represents the reward functions, where the outcomes for both destructive and defensive players are expressed as individual real values. These values can be positive or negative, indicating either gain or loss. Positive values signify gain, whereas negative values indicate loss.
- X denotes a collection of terminal places, and $X \cap P = X$. A place is classified as terminal when not connected to subsequent transitions.
- $\lambda = \{\lambda_1, \lambda_2, \lambda_3, \ldots, \lambda_x\}$ indicates the number of transitions per unit of time, with x representing the total number of transitions.
- I denotes the initial state of IoT players.
- U denotes the utility function of IoT players.

Definition 2 (Action and Place set of any IoT device at Edge layer): Let A^k represent the set of actions and Pk as the set of places for player k, we can represent the place set for IoT device k as the union of all actions that the IoT device can execute from any state $p \in P$. This can be expressed as:

$$P^k = \bigcup_{a \in A^k} p_a^k, \tag{2}$$

where p_a^k is the action a taken by player k at place p. Similarly, the action set can be expressed as:

$$A^k = \bigcup_{p \in P^k} a_p^k, \tag{3}$$

where a_p^k is an action set of any kth IoT sensor placed at p.

Definition 3 (Strategy and Strategy Set of IoT Devices at Edge layer): Strategies represent the collection of actions that an IoT device may employ while it operates. These strategies are termed "mixed strategies" when there is a specific probability associated with the choice of each strategy. Let S^k be a mixed strategy of kth IoT device. Then,

$$S^k = \left[\pi\left(a_1^k\right), \pi\left(a_2^k\right), \ldots, \pi\left(a_w^k\right) \right], \tag{4}$$

where a_1^k is the probability of selecting action a_1 of kth IoT device and w represents, the total action required as per problem, that is $w = |A^k|$.

$$S^k = \left[\pi\left(a_{p_1 \ i_1}^k\right), \ldots, \pi\left(a_{p_1 \ i_{|p^k|}}^k\right), \ldots, \pi\left(a_{p_{|p^k|} i_{|p^k|}}^k\right) \right], \tag{5}$$

where $\pi(a_{p_1 i_1}^k)$ denotes the likelihood of strategy i_1 being executed at place p_1 by IoT device k. The complete set of

strategies for the entire game involving N players can be represented as $S = (S^1, S^2, \ldots, S^N)$, where S^1 refers to the strategies employed by the first IoT device.

Corollary 1 (Probability of all Choices): The sum of probabilities for all available choices at any given node $p \in P$ will equate to one, which can be expressed as:

$$\sum_{a_i \in a_p^k} \pi\left(a_{p, \ i}^k\right) = 1. \tag{6}$$

Corollary 2 (Terminal Nodes): In the case of terminal nodes, the action set for each IoT device becomes empty, and the final payoff is computed. Therefore, for the kth IoT device, any terminal node $z \in Z$ will have an empty action set denoted as $\varnothing_z^k$. The utility function $U^k(R^k(a), \ p_0)$ for the kth IoT device starting from the initial node p_0 is simplified to $U^k(R^k(a))$ at the terminal node, resulting in the calculation of the final payoff.

Definition 4 (Reward Calculation): Reward obtained by kth IoT device at place p is expressed as:

$$R^k\left(p^w\right) = \sum_{o_i \in O} r_p^k(o_i) + \sum_{t_j \in T^w} r^k\left(t_j\right). \tag{7}$$

where O is the token set with time instant w at place p, the number of tokens passed within time window w is represented as T^w.

Discounted factor $\Delta \in [0,1]$ is also added to finish the game in finite time. Given any strategy s, the token is m level above the terminal node of SGN from current time stamp w. Expected utility of IoT device k from current time w can be calculated as:

$$\begin{aligned} U_w^k\left(\pi, \ p^w\right) &= E\left[R^k\left(p^w\right) + \Delta R^k\left(p^{w+1}\right) + \Delta^2 R^k\left(p^{w+2}\right) \right. \\ &\quad \left. + \cdots + \ \Delta^m R^k\left(p^{w+m}\right) \right], \\ &= E\left[\sum_{n=0}^{m} \Delta^m R^k(p^{w+n}) \right], \end{aligned} \tag{8}$$

where the expectation operator E computes the average of the probabilities employed in selecting transitions within the SGN. Consequently, if the kth IoT device decides to execute an action with a probability of $(\pi^k(p^{w+n}))$, it will receive the corresponding reward $(R^k(p^{w+n}))$. The reward at any place p can also be calculated using the probabilities as follows:

$$\begin{aligned} R^k(p) &= \sum_{t^1 \in T^1, \ldots, t^n \in T^n} \pi^1\left(p, t^1\right), \pi^2\left(p, t^2\right) \ldots \\ &\quad \pi^n\left(p, t^n\right) r^k\left(p; t^1, \ldots, \ t^n\right). \end{aligned} \tag{9}$$

D. SGN Formation in Smart Homes

The formation of SGN in smart homes is a data-driven process. IoT devices in smart homes when triggered due to some critical event like a fire or doorbell rings in smart homes then dynamic SGN will be created or SGN of that triggered device can be added to dynamic complete SGN. Moreover, one IoT device may require data from another IoT device based on the problem statement. Therefore, to construct dynamic

SGNs, perfect information on different smart home devices is required.

A tree-based data-driven multilevel SGN graph $G(V, E)$ is formed based on IoT devices in the smart home. Let n be the number of IoT devices and V be the set of vertices of SGN that map it to the next level directed node with the help of E edges. The leaf vertex or node is defined when $E_v = \varnothing$ if $v \in V$. Furthermore, the vertex set V can be partitioned into $(n + 1)$ disjoint sets, represented as V_i and $i \in n$ is a set of vertices required by i^{th} IoT device in smart homes for its functioning. In addition to that extra vertex V_{n+1} represents a set of all terminal nodes in the formation of data-driven dynamic SGN graphs. Finally, at each vertex V of the SGN graph, a unique value is defined for reward to calculate the final payoffs at terminal nodes based on the path from the root node to the leaf or terminal node.

E. Construction of Complete SGN for Different Scenarios in Smart Homes

1) Level 1: Data-driven SGN graph for the triggered IoT device remains the same with the initial vertex v_0, whenever an IoT device is triggered in smart homes. A triggered list of n IoT devices in the smart home is represented as a data-driven triggered list $DDTL = \{L_1, L_2, L_3, \ldots, L_n\}$. Let P consist of a set of edges, meant for joining two different SGNs. P_{mn} represents the linking of mth IoT device with n^{th} IoT device. Payoffs will be calculated based on Definition 4 and the action set is defined based on the data-driven 11 tuple element set in Definition 1.

2) Level 2: After the formation of Level 1 the IoT device L_1 has the following three options:

- *No action:* If $l_2 \notin DDTL$, that means no element is present in the DDTL. Therefore, the decision is based on available SGN. The game will then move to any one of the leaf nodes of the triggered l_1 device.
- *Data-driven SGN addition:* If $l_2 \in DDTL$, then SGN of l_1 IoT device should be included in the complete SGN graph. Moreover, the current state vertex of the l_1^{th} IoT device must add the l_2^{th} IoT device SGN so that the game will end at the leaf node of l_1^{th} IoT device.
- *Crack SGN:* If l_2 has completely vanished from DDTL, then SGN of the l_2^{th} IoT device will be removed from the complete SGN graph. Subsequently, the game will again commence from edge connecting SGNs of the l_2^{th} and the l_1^{th} IoT devices.

Finally, at Level 1, the number of vertices V available in the complete SGN graph for smart homes will be updated as

- $V = V$; if no action.
- $V \uplus (V) (P_{12})$; if new SGN incorporated.
- $V = V - (P_{12})$; if SGN has been removed.

3) Level 3: This level is created from the data-driven information at Level 2. Let us assume that the SGN graph currently is at level u ($1 < u \le w$), here w is the maximum possible level of the SGN graph. The linking of vertices at level u can be represented as $P = \{P_{12}, P_{23}, P_{34}, \ldots, P_{(u-1)(u)}\}$. Hence $P_{(u)(u+1)}$ will be defined using the following possible actions at level u.

- $V^{u+1} = V^u$; no action is required because of no $P_{(u)(u+1)}$ link and game will finish at leaf node of the u_{th} IoT device.
- $V^{u+1} = V^u \uplus V(P_{(u)(u+1)})$; new SGN added at stage $u+1$.
- $V^{u+1} = V^u - V(P_{(u-1)(u)})$; if previous SGN has been removed at stage $u+1$.

Therefore, in a data-driven SGN graph, for every node, a unique path P_v is always available. In simple words, a vertex in an SGN graph will continue its path based on data inputs until $v_u \in V$ and $v_u \in V_{n+1}$. After this, the smart home environment will choose an action from the SGN 11-tuple set in Definition 1. Using previously data-driven theoretical mechanisms, in a smart home-based environment, SGNs can be modified and the system can make decisions throughout the life cycle.

F. Nash or Game Equilibrium

Due to mixed strategies, any game has at least one Nash equilibrium vector set. In a smart home environment, mixed strategy for dynamic SGN with Q matches is formalized as:

$$M^* = \left(M^{1*}, M^{2*}, M^{3*}, \ldots, M^{Q*}\right). \tag{10}$$

The total reward for i^{th} player is

$$R^i\left(M^{1*}, M^{2*}, \ldots, M^{(i-1)*}, M^{(i*)}, M^{(i+1)*}, \ldots, M^{Q*}\right). \tag{11}$$

For any player i, M^i is the alternative strategy and the Nash equilibrium strategy is M^{Q*}. Moreover, as per our dynamic constructed SGN in Definition 1, there is Nash equilibrium for a smart home mixed strategy environment with all information. Since the SGN graph consists of IoT devices and each can act as a player with a finite set of actions and states of each IoT device's own SGN are also finite, we can say that it fulfills all the requirements of the proper game with Nash equilibrium for a certain set of mixed strategies.

G. Action Set, Place Set, and Reward Generation

Meanings of each place and actions are described in Table II and Table III, respectively. Each action performed at any given place is associated with a specific reward value. Fig. 2 displays the reward rates for all sensors, contingent on their locations and the actions to be undertaken.

Action set, place set, and reward rates for each transition are provided for individual sensors. These individual sensors act as players in the proposed smart home environment. Whenever, any action has to be taken based on the trigger of an individual sensor, inputs from other sensors are also taken so that the resultant action is most effective. Moreover, when more than one sensor is involved in taking any final action, a complete SGN is created by the system. The resultant action will be decided based on the subgame perfection of all sensors involved. Smart home consists of multiple sensors such as bed chair sensors, fire sensors, door sensors, body sensors, motion sensors, and RFID sensors. The data-driven dynamic SGNs for different events, considering all possibilities are shown in Figs. 3-6.

Bed / Chair Sensor (BS)

Actions	OFF	ON	S_OFF
Yes	-1	1	-1
Alert OFF	2	-1	1
Check MS	1	0	2

(A)

Motion Sensor (MS)

Actions	OFF	ON	S_OFF
Yes	-1	1	0
Alert OFF	1	-1	1
No Motion	2	-1	-1

(B)

Fire Sensor

Actions	Yes	NO	S_OFF	SMOKE
Initiate Water	[2,3]	[-1,-1]	[-1,-1]	[-1,-1]
Alert Inmate	[3,-1]	[-1,-1]	[1,-1]	[2,-1]
Alert Fire Services	[1,2]	[-1,-1]	[2,1]	[1,1]
Alert Neighbor	[0,1]	[-1,-1]	[0,0]	[0,0]

[BS / MS = Alert, BS/ MS = No Motion]

(C)

Door Sensor

Actions	ON	OFF	Open	Force_Open
Alert Visitor	[0,1]	[-1,-1]	[-1,-1]	[1,1]
Alert Inmate	[-1,1]	[-1,-1]	[1,-1]	[2,-1]
Alert Police	[-1,-1]	[-1,-1]	[-1,1]	[3,2]
Alert Neighbor	[-1,-1]	[-1,-1]	[-1,0]	[0,0]

[BS / MS = Alert, BS/ MS = No Motion]

(D)

Body Sensor (WS)

Actions	Normal	Fluct.	Emerg.
Alert Inmate	-1	0	0
Alert EMS	-1	-1	2
Alert Doctor	-1	1	1
No Alert	1	-1	-1

(E)

RFID Sensor

Actions	FULL	EMPTY	N_EMPTY	NEW
Ask Inmate	-1	2	1	2
Alert Mart	-1	1	0	0
Alert Doctor	-1	0	-1	1
No Alert	1	-1	-1	-1

[BS / MS = Alert, BS/ MS = No Motion]

(F)

Fig. 2. Reward generation table of all sensors when SGN triggered dynamically (A) Reward-based bed/chair sensor triggering (B) Reward-based motion sensor triggering (C) Fire sensor triggering rewards (D) Door sensor triggering and associated function-based reward generation (E) Body sensors based reward generation (F) RFID sensors based triggering for different scenarios.

TABLE II
PLACE SET OF ALL SENSORS

Sensor	State	Description
Bed/Chair Sensor	OFF	Bed/Chair is empty.
	ON	Someone is sitting on a bed/chair.
	S_OFF	Sensor goes OFF suddenly. When someone leaves the bed/chair.
Motion Sensor	OFF	There is no motion in the home.
	ON	Someone is in the home.
	S_OFF	Someone just left the home.
Fire Sensor	YES	There is a fire in the home.
	NO	There is no fire in the home.
	S_OFF	Fire just stops.
	SMOKE	There is smoke in the home.
Door Sensor	ON	Someone is at the door.
	OFF	No motion at the door
	OPEN	Door is opened by someone.
	FORCE_OPEN	The Door lock is broken, and someone forcibly enters the home.
Body Sensor	NORMAL	Every wearable sensor is giving normal readings.
	FLUCT.	There are fluctuations in body wearable sensor data.
	EMERG.	There is a medical emergency in the home.
RFID Sensor	FULL	Supplies are full.
	EMPTY	Supplies are empty.
	N_EMPTY	Supplies are nearly empty.
	NEW	User asked for some new supplies.

Fig. 3. SGN at edge node for health event occurrence and its dependability on body sensor (WS).

Rewards come in varying values, where a higher reward value indicates a greater likelihood of selecting the associated action. The magnitude of the reward value reflects the priorities of actions. Tables II and III outline the place and action sets for different sensors. Moreover, the reward generation on triggering 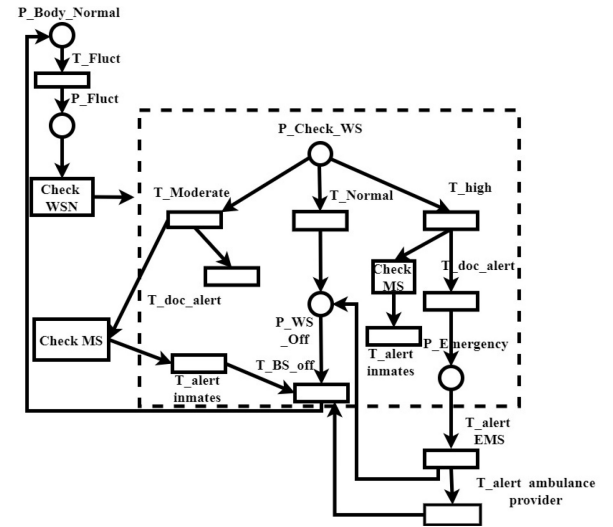of different sensors is shown in Fig. 2. If the reward values are 3, 2, and −1, the reward value of 3 has higher priority than the reward value of 2. If the reward value is −1 that means no action should be taken. Positive reward value should be carried out if possible. Based on these reward values, the final strategy will be developed. In the case of complete SGN, all reward values are calculated according to Definition 4, and the action with the highest reward value is taken. Moreover, procedural steps for dynamic SGN creation in smart home applications are given in Algorithm 1.

IV. PERFORMANCE EVALUATION

SGN-based solution of IoT smart environments has a wide variety of application scenarios. Even in smart homes for

TABLE III
ACTION SET OF ALL SENSORS

| Sensor	Action	Description
Bed/Chair Sensor	Yes	Someone is sitting on bed/chair.
	Alert OFF	Put bed/chair sensor alert to off.
	Check MS	If BS is OFF check the motion sensor for any motion in the home.
Motion Sensor	Yes	Someone is in the home.
	Alert OFF	Put motion sensor alert to OFF.
	No Motion	There is no one in the home.
Fire Sensor	Initiate Water/Sand	Start spraying water/sand where fire has been sensed.
	Alert Inmate	Alert if someone is in the home to get out.
	Alert Fire Services	Alert fire services automatically.
	Alert Neighbor	Alert neighbor to get out of their respective homes.
Door Sensor	Alert Visitor	Alert visitor and take a photograph.
	Alert Inmate	If someone is in the home, alert him/her about visitors.
	Alert Police	Alert the police about unauthorized entry and send photographs.
	Alert Neighbor	Alert neighbors about unauthorized entry into the home.
Body Sensor	Alert Inmate	If someone is in the home, alert him/her about the medical situation.
	Alert EMS	Alert Emergency Medical Services about medical conditions.
	Alert Doctor	Alert the doctor about the medical condition in the home.
	No Alert	Everything is normal, no need to generate any alert.
RFID Sensors	Ask Inmate	If someone is in the home, ask him/her about the supplies.
	Alert Mart	Alert shopping mart to send supplies requested by users.
	Alert Doctor	Send data of supplies consumed by user to doctor so that calorie consumption data is available to doctor.
	No Alert	Everything is normal, no need to generate any alert.
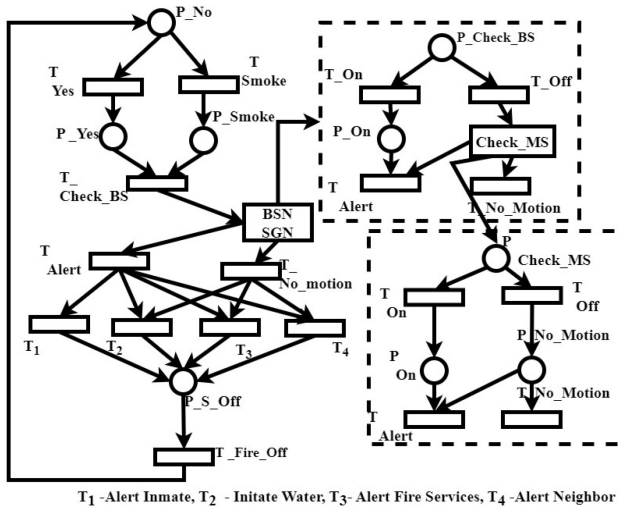
Fig. 4. SGN at edge node for fire sensor and its dependability on bed/chair sensor (BS).

Fig. 5. SGN at edge node for theft detection and its dependability on motion sensor.

senior citizens, hundreds of sensors can generate thousands of scenarios. To study the applicability of SGN in decision-making for IoT smart environments, the six most influential sensors are used and sensor-based datasets from state-of-the-art were also used to simulate the smart home environments and different scenarios. Net Logo with its wide suitability in creating networks is used for simulating SGN-based IoT smart environments.

A. Experimental Setup and Protocols

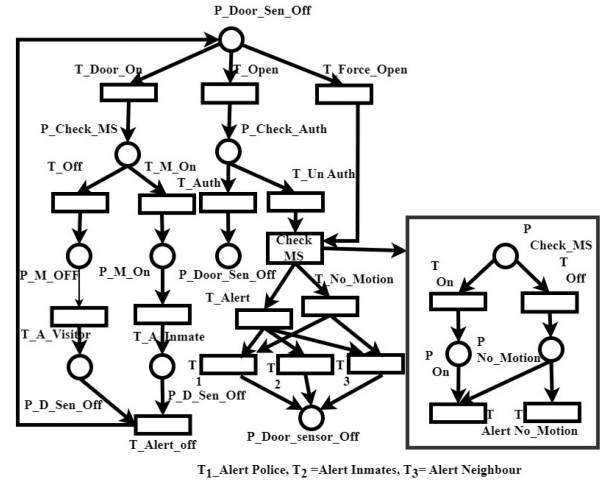Net logo 6.3.0 interface has been used to provide input from different sensors and output as final action from the

system [34]. A complete SGN graph has also been created using individual graphs of each sensor as shown in Figs. 3-6. Definitions explained in the mathematical part of the proposed system are implemented at the backend of the Net logo. Sub-game perfection methodology has been used in the Net logo coding. Initially, optimization of each sensor action is conducted, considering the reward values specific to each sensor. Subsequently, a comprehensive SGN is constructed, and the ultimate reward value is computed based on the sensors utilized in forming the complete SGN. In this way, individual sensor actions and complete SGN actions are optimized to attain sub-game perfection in the
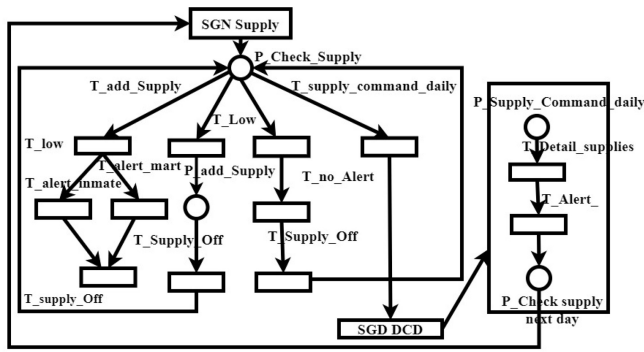
Fig. 6. SGN at edge node for article consumption and its dependencies on RFIDs.

system. Fig. 7 shows the interface developed in the Net logo to experimentally evaluate the proposed SGN method for smart environments. *Choose* button has been used to add a place set of each sensor, *Output* box has been used to show the final action of all individual sensors as well as the complete SGN graph, *3D Graph* is used to show the generation of complete SGN graph, *Auto Selection* button automatically selects places of all sensors based on predefined probabilities and *Update Button* automatically updates the complete SGN graph and final actions if some changes are made to place a set of all sensors by the user or *Auto Selection* button.

1) Results From Net Logo Evaluation: *Auto Selection* and *Update* buttons are kept on for 1000 ticks and different results are stored. Results encompass the frequency of place utilization by various sensors and the ultimate actions taken by the complete SGN graph. In the experimental assessment of the proposed system, the "Auto Selection" button indicates the number of times different places were selected, as depicted in Fig. 7. By considering the various place sets of all sensors, the Net Logo software offers recommendations for final actions. Fig. 8 provides insights into the number of final actions carried out by the proposed system.

2) SGN-Based Decision Making at Edge Layer vs. Cloud Layer: The temporal delay parameter is adopted to create SGN-based automated decisions. It's the total time required for SGN generation and decision-making. $T_{SGNformation}$ denotes the time for generating SGN and $T_{decisionmaking}$ denotes the time required for decision formulation. Therefore, temporal delay at the edge device can be represented as:

$$Temporal\ delay = T_{SGN\ formation} + T_{decision\ making}, \quad (12)$$

where $T_{decision\ making}$ denotes the time required after SGN creation for delivering the information to the concerned entities (fire departments, police departments, nearby homes, and grocery stores).

Cloud-assisted IoT-enabled smart home SGN creation environment requires transferring of various events happening information by the following carbon footprints of the core networks resulting in a rise in delivery time (Temporal delay $= T_{SGN\ formation} + T_{decision\ making} +$

$T_{transfertime}$). Moreover, cloud-based tasks such as smart factory data instances can adopt the SGN model for various hazards. Our proposed model can be compared with other decision models (like artificial neural network ANN, support vector machine (SVM), and K-nearest neighbor (KNN)) at the cloud layer in the future. On the other hand, edge avoids back-and-forth traffic between the cloud and entities in the smart home environment. This limits the bandwidth but increases the efficiency of the network. Fig. 9 depicts that the proposed IoT-enabled fog-assisted SGN-based smart home monitoring system is far more effective in delivering information to the entities associated with the smart home environment as compared to the cloud-based smart home SGN system. Moreover, the low value of delay time indicates the effectiveness of the SGN-based smart home monitoring strategy in our proposed system.

B. System Evaluation

The proposed smart home system (Data Driven SGN) is evaluated on different smart home datasets, because of multiple events: Kasteren [35] and Aruba [36]. The interaction of the user and different sensors in the smart home is gathered using multiple sensors like motion, cabinet, contact switch, etc. Moreover, the Game Plan [37] software kit is used for activity detection. SGN graph and reward tables are prepared for the above-mentioned sensors to compute the Nash equilibrium as per Section III-C–III-E. Sub-game perfection method plays a pivotal role in calculating Nash equilibrium for each smart home sensor-based sub-game. The number of activities correctly classified by the proposed system is compared with other state-of-the-art methodologies using five cross-validation methods for rigorous results because of the smaller dataset. Moreover, many sequences of different sizes triggered during sensor interaction were also taken into consideration (not the activity) for evaluation.

1) Evaluation Statistical Measures: The proposed SGN-based smart home events results can be compared with learning classifiers like AR-CbC, ET-KNN, KNN, and PNN [36]. Statistical parameters like *precision*, *recall*, *F1 score*, and *accuracy* play a significant role in determining the applicability of the proposed method in smart home environments [38]. Datasets comprise 6477 instances of Aruba for determining 11 activities in smart homes. 245 instances of the Kasteren dataset for 7 activities another Kasteren dataset of 272 instances for 10 activities. The set of activities performed by the user in all datasets along with complete SGN created for separate activities using NetLogo 6.3.0 are stored in an 11th Gen Intel Core i7-11700 @ 2.50GHz system. The stored complete SGN for different activities is important to identify the activities in smart homes. On the other hand, other classifiers' results are calculated using Python with 16GB of RAM. Table IV shows the comparison of the decision-making efficacy of the proposed system with other state-of-the-art classifiers using the above-mentioned data sets. Moreover, k-fold cross-validation methodology is applied on all datasets to yield rigorous results.
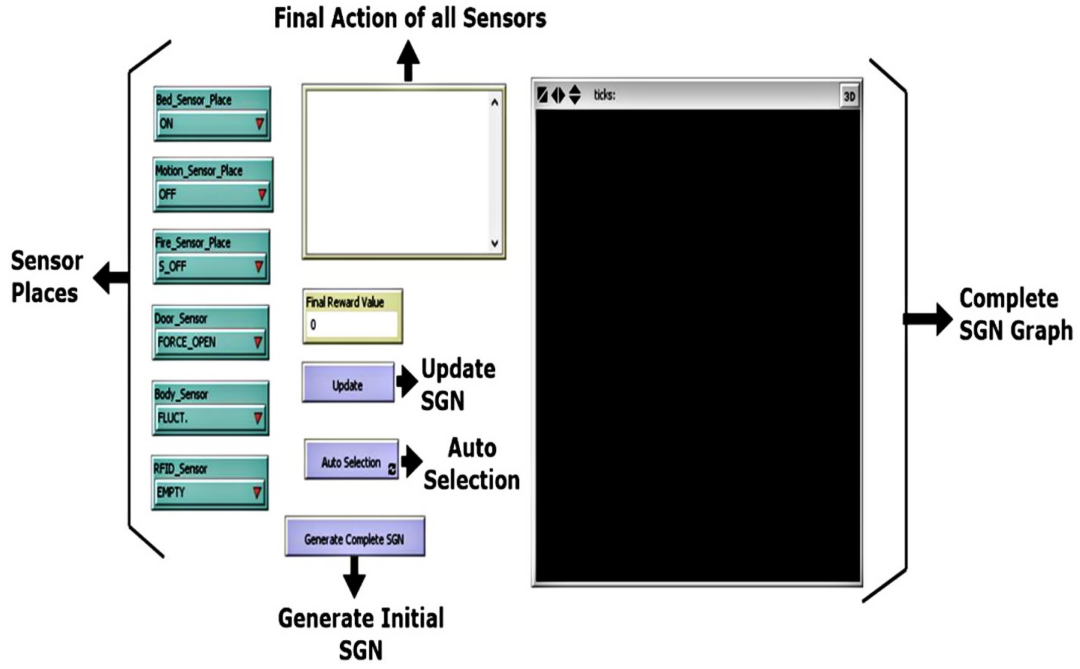
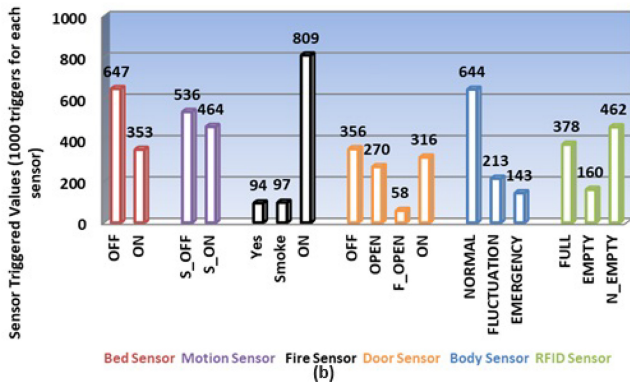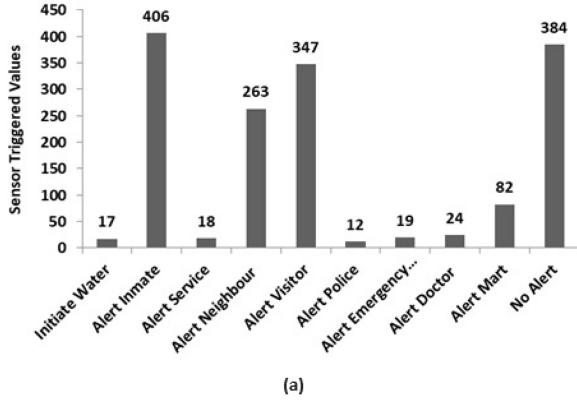Fig. 7.   Net logo-based simulation environment for our proposed model.

(a)

Fig. 9.   Event-based temporal efficiency in proposed SGN-based smart home environment.

(b)

Fig. 8.   Cardinality of (a) Final action suggested by sensors (b) Each sensor triggered values based on input to Netlogo.

2) Energy Efficiency at Edge Layer: In our proposed system, energy efficiency at the edge gateway is mathematically computed as:

$$T_{m+1}^i = \alpha t_m^i + (1 - \alpha)T_m^i; 0 < \alpha < 1, \quad (13)$$

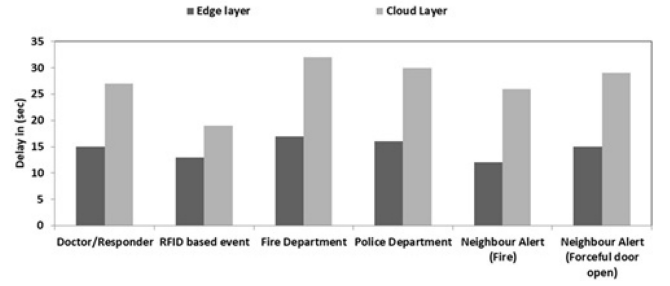$$t_{m+1}^i = T_{m+1}^i + \Delta t^i, \quad (14)$$

where the inactivity mode of IoT nodes is estimated in two levels. Level 1 predicts the length of an IoT node's next inactivity interval based on previous history. Level 2, based on different criteria the actual estimated value of the inactivity interval is determined. Here, T_{m+1}^i is expected value of mth IoT node's $m + 1^{th}$ inactivity interval, and t_m^i be the actual value calculated of mth inactivity interval. The exponential mean of the recorded duration of prior inactivity intervals is used by the IoT nodes to predict T_{m+1}^i of each $IoTnodes^i$ linked to it. α is the regulating parameter that affects how rapidly the historical value deteriorates. The sensor type in a particular application determines α value. In most of the cases, the value of α is set closer to zero. The value of the factor Δt^i in periodic sensors is based on numerous values like information quality, energy capacity, conflict factor, etc. [39]. In our proposed system, the energy efficiency is calculated based on the Aruba dataset, while considering both inactivity and without inactivity criteria. The result in Fig. 10 depicts that while applying inactivity criteria the energy consumption efficacy is significantly enhanced by an average of 39 mJ/nodes.

TABLE IV
STATISTICAL MEASURES OF ACTIVITY RECOGNITION IN SMART HOME BASED ON THE PROPOSED METHOD AND OTHER CLASSIFIERS

Datasets	Folds	Approaches	Precision(%)	Recall(%)	F1 score {0,1}	Accuracy(%)
Aruba	Five Fold	**Proposed**	**85.67**	**83.47**	**0.82**	**93.45**
		AR-CbC	78.55	75.38	0.76	91.08
		ET-KNN	73.22	72.55	0.71	90.72
		KNN	71.08	71.04	0.69	88.77
		PNN	69.06	67.87	0.68	88.28
Kasteren (7 activities)	Five Fold	**Proposed**	**95.07**	**93.07**	**0.93**	**95.34**
		AR-CbC	90.12	89.96	0.89	92.88
		ET-KNN	88.29	86.87	0.83	91.89
		KNN	89.06	82.12	0.83	88.25
		PNN	89.64	83.04	90.67	
Kasteren (11 activities)	Five Fold	**Proposed**	**92.55**	**92.07**	**0.91**	**95.32**
		AR-CbC	89.67	91.22	0.88	92.33
		ET-KNN	90.23	85.87	0.84	90.03
		KNN	90.09	83.22	0.82	89.22
		PNN	88.50	81.46	0.82	90.27
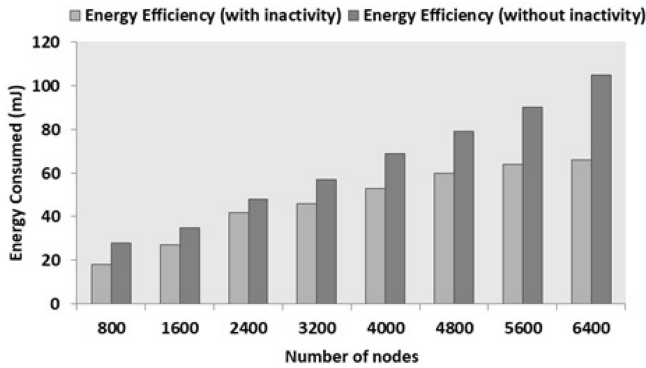
Fig. 10. Energy efficiency in proposed SGN-based smart home environment.

TABLE V
STATISTICAL RESULTS ALERT GENERATION

S.no	Parameters	Value
1	False Positive Alert	3.15
2	Sensitivity	88.47
3	Specificity	94.27
4	Precision	91.23
5	Coverage	98.12
6	Mean Absolute Error	3.14
7	Root Mean Square Error	2.53
8	Relative Absolute Error	7.84
9	Root Relative Squared Error	3.48

3) Statistical Analysis of Alert Generation: In this section, we assess the system's statistical parameters concerning alert generation for the relevant entities associated with the smart home emergency management environment. The primary objective of the statistical analysis of the alert generation process is to determine the proportion of "false positive" alerts about the total number of generated alerts. Table V reveals that only 3.15% of the alerts fall into the category of false positives.

The parameters such as sensitivity (88.47%), specificity (94.27%), precision (91.23%), and coverage (98.12%) elucidate the accuracy of the alert generation procedure. Furthermore, the minimal values of various error parameters indicate that the SGN-based transition mechanism proves highly effective in addressing emergencies within a smart home environment as shown in Fig. 10.

C. Discussion

Our proposed system conducts an SGN-based evaluation in the smart home environment, characterized by dynamic final actions. This dynamic aspect is realized by the dynamic creation of a complete SGN graph through the integration of individual sensor graphs. The Net logo is used to create a dynamic complete SGN using six sensor readings in the smart home environment for different events. Net logo-based cardinality results in Fig. 8 provide final actions based on the reward calculated at the terminal node. Moreover, the SGN-based model at the edge layer provides real-time decision-making for various events in the smart home environment. The simulation results also depict that the SGN-based smart home environment is very effective in generating alerts for different cases and the action taken by SGN is completely dynamic. In addition to that, decision-making is far more effective in our proposed system when compared with other decision models. The temporal delay and energy consumption are significantly reduced using the SGN data-driven model at the edge layer.

V. CONCLUSION AND FUTURE WORK

A smart home environment employs multiple sensors collaborating to perform actions in response to diverse event detection scenarios. This paper presents a novel edge-assisted IoT-enabled SGN-based smart home environment for implementing dynamic action strategies apt for various real-time occurrences of events such as fire, theft, patient health, motion sensors, and grocery information. The key highlights of the paper include (i) modeling data-driven smart home environments using n-player game theory and (ii) real-time decision-making through edge computing followed by timely customer-oriented alert generation. The applicability and efficiency of the proposed framework are validated through a simulated environment using NetLogo which provides promising results. Future directions for the current work can be expressed in points. Firstly, the temporal delay efficacy of the

proposed system can be further compared with the state-of-the-art decision models for better decision-making. Secondly, the economic aspect of the proposed model for other smart city applications needs to be explored [40]. Finally, research can be further extended for energy efficiency, security, and software development for real-time smart home applications.

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