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Applied Fuzzy Knowledge Graph Model for Monitoring Smart Home Under Uncertain Environments

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Abstract

Smart home provision faces many challenges, resulting from the growing demand for monitoring smart home services in uncertain environments, such as rural areas, and regions with high humidity, pollution, and unstable electricity supply. Effective data processing in decision-support cyber–physical systems for smart environments is challenging given that the raw data [collected from context-aware networked sensor-based systems under dynamic uncertainty] is typically imprecise, inaccurate, and potentially incomplete. Addressing this challenge requires effective data processing. To address this challenge, in this paper we present our proposed novel *Fuzzy Knowledge Graph Model* to enable the processing of raw data derived from a smart home environment. The experimental testing of the proposed model includes data preparation, reasoning, and action control. To evaluate the performance of the proposed model we utilise four evaluation metrics: *accuracy*, *precision*, *recall*, and *F1-score*. The evaluation shows that the proposed model achieves good statistically significant results in terms of accuracy (recall: 100% with low false positives; precision: 94.74%), leading to an F1-score of 97.3%. The results indicate that the proposed model demonstrates high levels of performance in terms of accuracy, with good precision, recall, and F1-score. Moreover, the reported results confirm the reliability, stability, efficacy, and utility of our proposed model, which we posit has the capability to be generalised to smart home domains.

Keywords: decision-support systems; learning and reasoning method; context awareness; dynamic uncertainty; smart environments; fuzzy knowledge graphs

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1. Introduction

Smart home provision is a multi-factorial challenge driven by the increasing demand for the provision of multiple services, exacerbated by limitations in the availability of physical and financial resources. Moreover, the rapid advances in medical technologies typically involve increasingly complex care pathways and services. The challenges experienced by smart home systems and professionals are further exacerbated by increasing complexity in terms of conditions experienced by an ageing demographic [1,2].

The smart home, when viewed from the perspective of this study, is a topic closely interrelated with social-care provision [3], which is increasingly being considered in terms of remote patient monitoring in a domestic setting. Such an approach of applying monitoring highlights the need for a *smart home* to be in an expanded *smart environment* [1]. An expanded smart environment may incorporate, for example, a smart city, hospital, residential facility, and domestic setting (i.e., a home) under an uncertain environment. When considering smart environments, such an environment may incorporate interlinked smart Internet of Things (IoT) in systems implemented in FOG and edge computing systems [4,5]. In this research the data source is limited to a smart home, as discussed in Section 3.1, where data collection and processing is introduced.

While smart home provision forms an important underlying factor that motivates this research, the primary focus of this research lies not in smart home provision but in addressing the challenges inherent in the effective and intelligent processing of raw sensor-derived data obtained using context-aware sensor-based networked cyber–physical systems [6] for smart environments [1].

Given the multi-factorial and domain-specific nature of sensor-based networked systems [which include body-area networks in smart environments] it is beyond the scope of this paper to provide a detailed discussion on such systems and the related sensor technologies. In summary, smart environments have gained significant interest and traction [1,7,8], with a multiplicity of interconnected applications which enable autonomous function control using a centralised framework. The developments in sensor-based networked cyber–physical systems are implemented in, for example, *wide-area networks*, *local-area networks*, and increasingly *body-area networks*, where a mobile phone may collect and preprocess sensor data and transfer the data to a remote server for final processing [1]. For a detailed exposition on sensor technologies, including sensor types, networking technologies, testing, validation, and potential applications, see [9–15].

A further significant issue is the inherent uncertainty within the data, which is driven by continuous environmental changes and unpredictable human behaviours. For instance, motion sensors may misinterpret the presence of a pet as human activity, leading to inappropriate system responses. The ability to process imprecise information and make flexible decisions under uncertain conditions has thus become a crucial requirement for smart home systems to function effectively.

To address these challenges, the use of *knowledge graphs* (KGs), and the developments in *fuzzy knowledge graphs* (FKGs) [16], has emerged as a promising solution. By combining the strengths of fuzzy set theory with KG structures [17], an FKG provides an effective methodology to model relationships between devices and data while managing uncertainty and imprecision. This approach enables the provision of flexible and context-aware decision support in a smart environment system constrained by the need to process incomplete or ambiguous data, thereby improving system adaptability and 'real-time responsiveness'.

In this paper we present our novel *Fuzzy Knowledge Graph Model* (hereafter termed FKGM), where the integration of FKGs into data processing systems enables significant potential advantages for a smart home. The contributions made by our study and the proposed novel FKGM model may be summarised as follows:

- *Optimised system performance*: The proposed data processing method provides an effective basis upon which the management and processing of dynamic imprecise, incomplete, uncertain, and potentially incorrect sensor-derived data in a smart environment may be realised.
- *Improved adaptive capability*: The proposed data processing method provides an effective basis upon which systems can adapt and respond to diverse and dynamically variable

environmental contexts. An evaluation of the adaptability and efficiency of the proposed model shows improvement in data processing and related user experience.

- *Enhanced user experience*: The proposed FKGM model importantly provides an effective basis upon which adaptive systems can "learn" from environmental changes, offering intelligent, flexible, and context-specific responses. Moreover, the proposed model is demonstrated in experimental testing predicated on an analysis using simulations in complex scenarios.

The remainder of the paper is structured as follows: related research is considered in Section 2. The proposed FKGM model is introduced in Section 3, with a scenario-based example implementation provided in Section 4. The implementation and evaluation strategies are provided in Sections 5 and 6, respectively. The results are set out with an analysis in Section 7 and a discussion in Section 8. Open research questions and directions for research are addressed in Section 8.1 along with practical managerial significance in Section 8.2. The paper closes with concluding observations in Section 9.

2. Related Research

In our review of related research, the literature review is limited to considering technologies that are relevant to the proposed FKGM model presented in this paper. Given that the fundamental principles that characterise such technologies are generally well known and understood, we provide references to where a comprehensive discussion may be found. The components are as follows: (i) *fuzzy sets* (FSs) [18,19]; and (ii) *fuzzy inference systems* (FISs) [20], which include *knowledge graphs* (KGs) and FKGs [21–26].

Turning to healthcare and diagnostics, the literature contains a multiplicity of methods and systems which have been applied to healthcare monitoring, as well as the related data processing. Such methods date back to the mid-1970s [27], where the physician's medical knowledge was represented by fuzzy relations between symptoms and diseases by Sanchez, as discussed in [28]. For a comprehensive discussion on fuzzy sets and applications, see [27,29,30].

FKG technologies combine fuzzy logic with traditional KG structures to effectively manage data uncertainty and ambiguity, resulting in improved performance in terms of decision support across various fields, as discussed in [27,31]. Decision-support systems combining fuzzy logic with reinforcement learning methods have unlocked promising new approaches, particularly when addressing extreme cases. However, traditional FKG models often rely on a single pair for inference, potentially limiting the accuracy of approximations, whereas our proposed FKGM model addresses this limitation by utilising multiple pairs, thereby strengthening the system's ability to classify new records that conventional rule-based systems might struggle to handle effectively [27,29].

An interesting study integrating *Q-learning* with *FKG pairs* (FKG-Pairs) was introduced by Long et al. in [32]. Here, the proposed method leverages Q-learning to learn from environmental interactions combined with the representational advantages of FKGs. The proposed FKGM model aims to enhance accuracy and efficiency in decision support under conditions of incomplete or uncertain input data. The results from the study demonstrated that this approach significantly outperformed traditional models when addressing extreme scenarios, highlighting its potential for widespread application in intelligent decision-support systems.

Khajeh et al. proposed a fuzzy logic-based control strategy for smart homes equipped with energy storage systems. The proposed system utilised battery energy storage systems connected via inverters combined with with flexible devices, such as air conditioning units and electric vehicles; the goal was to support frequency regulation and provide ancillary services to both transmission system operators and distribution system operators. Implementation employed a fuzzy logic control system to optimise power supply management while maintaining residents' thermal comfort and scheduling preferences. The simula-

tion results indicated that this method enhanced the economic efficiency of smart homes while improving grid reliability and stability in the presence of intermittent renewable energy sources.

Weerdt, in [33], considered the Internet of Things (IoT) as smart devices in smart environments in the context of the Semantic Web and satellite events, observing that this approach integrated heterogeneous data from smart devices in smart homes. Weerdt introduced a framework to leverage KGs to improve predictive capabilities in smart homes. The study focused on transforming data from IoT devices into KGs to provide a basis upon which machine learning algorithms could process heterogeneous data more effectively. By integrating external data sources and applying federated learning across multiple smart homes, the framework aimed to increase the accuracy of predictive models. The findings revealed that the use of knowledge graphs significantly enhanced the performance of predictive algorithms in smart home environments, demonstrating their potential in intelligent home automation systems.

Building on these advancements, recent studies have focused on integrating generative AI (GenAI) with FKG technologies, the aim being to enhance the functionality of smart environmental systems. In [34], the study explored the combination of hedge algebra and multilingual large language models to uncover hidden patterns in datasets, thus enabling the creation of adaptive, context-aware rules for decision-support systems. A prominent study demonstrated the transformational potential of multilingual large language models in GenAI systems by developing intelligent conversational agents for 'real-time' applications [35]. This work highlighted their ability to interact seamlessly with users across multiple languages, providing personalised dynamic responses. These developments underscore the synergy between GenAI and FKGs, empowering smart homes to intelligently process user inputs, extract actionable insights, and deliver tailored services with enhanced efficiency and adaptability.

3. Proposed Fuzzy Knowledge Graph Model

In this section we introduce the proposed FKGM model, including its data collection, data processing, implementation, and numerical examples, to clarify our posited method. We set out the key components of the FKGM model; specifically, we describe the model's architecture, outline the implementation steps, and provide numerical examples to illustrate how the model operates within a smart home system. An illustrative example of the proposed FKGM model applied to a typical IoT-enabled smart home is shown in Figure 1.

The data processing architecture for the proposed FKGM model is shown in Figure 2, where the *input*, *output*, *processing*, and *output monitoring* are modelled.

3.1. Data and Rule Processing

The data collected and processed in this study is set out in Section 4, while the sensor and data types in the control system used in the proposed FKGM model are presented in Section 5.

Given the domain-specific nature of sensor-driven raw data collection, sensor types, and data types, combined with the developments in *information technology* (IT) and the related *information communications technology* (ICT), it is beyond the scope of this paper to provide a detailed exposition on the sensor-driven data collection given that the sensors and data types are domain-specific. For a detailed discussion on sensor technologies, including sensor types, networking technologies, testing, validation, and potential applications, see [9–15].

Developments in IT and ICT have resulted in research into aspects beyond the scope of computer networks. A paper entitled "*A Comprehensive Review of IoT Networking Technologies for Smart Home Automation Applications*" [13] considers advances in micro-electro-mechanical systems (MEMSs) [14], which include micro-sensors, micro-actuators, micro-

electronics, and other micro-structures. There are sensor types that incorporate data reprocessing functionality in BAN [1] using, for example, the *Raspberry Pi*, which is a micro-controller board [36] that is well suited to a variety of projects, including automation, remote monitoring, and smart sensors [37]. The experimental hardware implementation is presented in Section 5.

Processing data [including, for example, temperature, humidity, light intensity, wind, precipitation] collected using a range of networked sensors is discussed in [38]. Key features are selected to construct the FKGs [39]. Training and testing datasets are generated after applying data preprocessing techniques and rule-generation mechanisms [40]. The testing data comprises samples generated using the rule-generation mechanism drawn from [41], based on the IF–$THEN$ rule structure [42]; the rules are shown in Table 1.

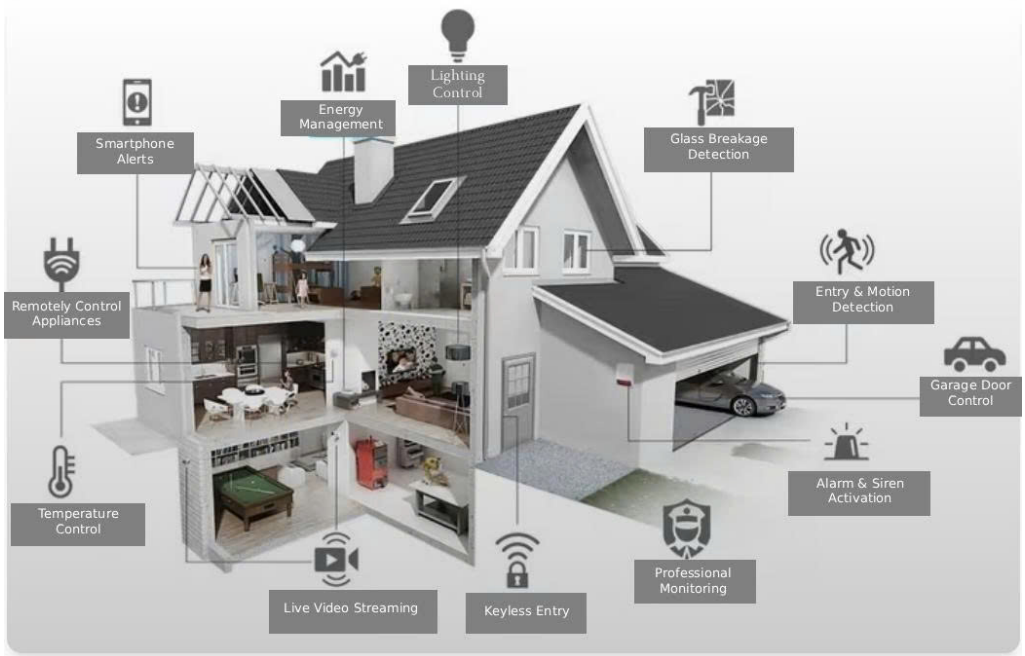

Figure 1. An illustrative example of the proposed Fuzzy Knowledge Graph Model (FKGM) as applied to a typical Internet of Things (IoT)-enabled smart home. The data sources will be interlinked with cloud-based systems, which include FOG and edge computing systems [5]. Data transfer will include the developing 5G and 6G mobile data systems, with data potentially preprocessed using body-area networks using, for example, a digital smart phone, where monitoring is not limited to Wi-Fi-enabled smart environments, but it may be exploited in an expanded smart environment, as discussed in Section 1. In such a scenario, the smart phone acts as a server enabling data collection, preprocessing, and transfer to a remote server(s) for further data processing.

Table 1. The fuzzy rule base, showing the rules and related attribute values combined with the output label.

Rule	S1	S2	$\cdots$	Sm	Output Label
R1	Low (1)	High (2)	$\cdots$	High (m)	1
R2	High (1)	Low (2)	$\cdots$	High (m)	2
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
Rn	Low (1)	Low (2)	$\cdots$	Low (m)	C

Note: S_i denotes the ith sensor input attribute, R_k denotes the kth fuzzy rule, m is the number of input attributes, n is the number of rules, and C is the number of control-state output labels.

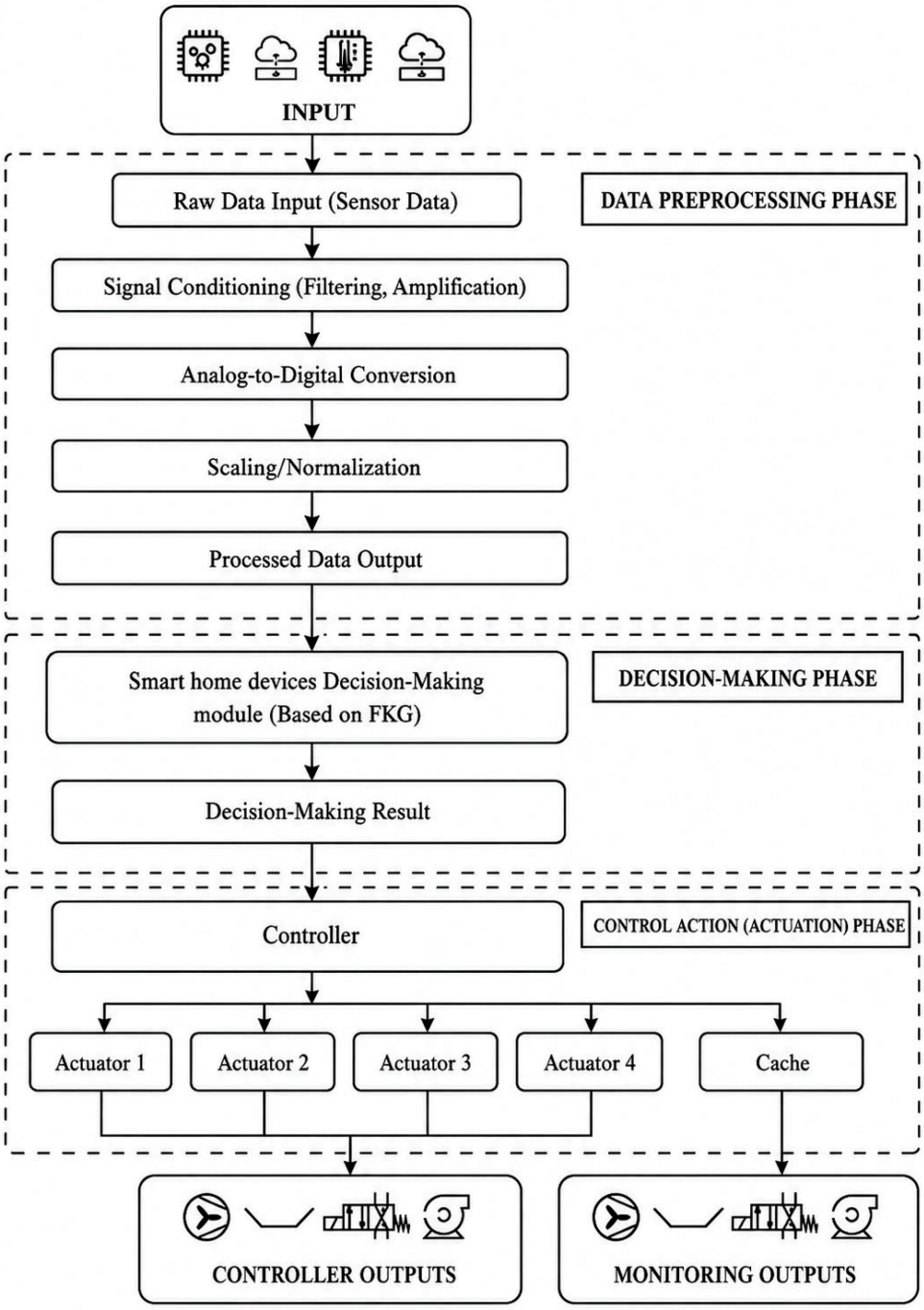

Figure 2. The data processing architecture for the proposed Fuzzy Knowledge Graph Model (FKGM), illustrating the input, output, and output monitoring.

The fuzzy rule base for the training dataset is detailed in Table 1; it shows (n) rules $(R_1, R_2 \ldots R_n)$ in the fuzzy rule base (m) for input attributes $(S_1, S_2, S_3 \ldots S_n)$, which represent the input attributes; where (i) each attribute is expressed through linguistic variable values, and (ii) the output labels are $(1, 2, 3, \ldots C)$, and represent control-state labels, as shown in the following example:

IF S_1 is "Very High$_1$" and S_2 is "Very High$_2$" and ... and S_m is "Very High$_m$"
THEN the output label = 1.

The semantic terms such as "Very High" are extensions of the "concept learning" paradigm, as discussed in [43], where the potential benefits derived from the use of this approach have been demonstrated and validated in practical weather-based examples.

The goal of this study is to determine the output label for new records, where the sensor data is input into the system derived from the control module for smart environment sensors. To realise this aim we propose our novel *Fuzzy Knowledge Graph Model* (FKGM), where the raw data is collected from sensors in a smart home environment model.

The proposed FKGM model is based on FKG technology, as discussed in [44]. FKG technology consists of three main phases: (i) the *data preparation* phase, (ii) the *data processing and decision-support* phase, and (iii) the *action-and-control phase*. The proposed model enables the system(s) to process data from sensors and provide appropriate decision-support combined with effective autonomous and flexible control of sensors. Details of the model are illustrated in Figure 2. The three phases can be summarised as follows.

Data preparation phase: In this first phase, sensor data are collected and processed through signal conditioning, which includes filtering and amplification, to ensure stable input signals. The sensor data is then scaled or normalised to a range of $[0 \ldots 100]$, facilitating further processing within the FKGM [45].

Data processing and decision-support phase: In the second phase, the system utilises the FKG to '*fuzzify*' the normalised data and apply fuzzy inference rules [16]. This process enables the system to handle ambiguous and uncertain data. The inference outcomes from this phase determine the control states of devices, such as OFF, LOW, $MEDIUM$, $HIGH$, and $VERYHIGH$, based on 'real-world' environmental conditions.

Action control phase: In this third phase, the results from the fuzzy inference [46] process are "*defuzzified*" [47] to derive specific values to control electrical sensors in the smart home. This ensures that the sensors operate according to the inferred decisions, providing a seamless and intelligent response to environmental changes [48].

3.2. The Proposed Model

To implement sensor control in a smart home system based on our FKGM model, strict adherence to the following steps is required:

3.2.1. Step 1: Data Collection

From the collected sensor data, relevant features [as identified above] for sensor control are extracted and stored in a database, which serves as the raw data source.

3.2.2. Step 2: Prepare the Fuzzy Rule Base

In this step, several tasks are carried out before constructing the FKG in the FKGM:

- *Data processing*: Raw sensor data is preprocessed to remove noise and inconsistencies.
- *Rule generation*: A mechanism is applied to generate rules for the fuzzy rule base.

3.2.3. Step 3: Representing the FKG

- Calculate the edge weight set by applying Equation (1):

$$A^t(X_iX_j \ldots X_n) = \frac{|\sigma(X_i) \to \sigma(X_j) \to \ldots \to \sigma(X_n) \text{ in rule } t|}{|r|} \tag{1}$$

  where $(1 \leq i \leq j \leq \ldots \leq n \leq m;\ t = 1, r)$, $(|r|)$ is the number of rules in the training dataset, and $\big(\sigma(X_i) \to \sigma(X_j) \to \ldots \to \sigma(X_n)\big)$ is the linguistic value of the attributes $\big(X_iX_j \ldots X_n\big)$.
- Calculate the edge-weight set to connect the input attribute labels and output labels in the FKG [49]. The edge weight $\left(B^t_{ij\ldots n}\right)$ is computed by applying Equation (2):

$$B^t_{ij\ldots n} = \left(\sum_{j=i+1}^{m} A^t_{ij\ldots n}\right) \times \min\left(\frac{|\sigma(x_i) \to l|}{r}, \frac{|\sigma(x_j) \to l|}{r}, \ldots, \frac{|\sigma(x_n) \to l|}{r}\right) \quad (2)$$

where $(1 \leq i \leq j \leq \ldots \leq n \leq m; t = 1, r)$ and the output label is $(l = \overline{1, C})$.

3.2.4. Step 4: Inference for Output Label Prediction

In step 4 we apply inference and reasoning to predict the output label(s). The process is as follows:

Calculate the relation weighting: The total weight $\left(\tilde{C}_{ij\ldots nl}\right)$ is determined by summing the weights of all relations connected to the output label $\left(B^t_{ij\ldots nl}\right)$ using Equation (3) and (4):

$$\tilde{C}_{ij\ldots nl} = \sum_{t=1}^{r} B^t_{ij\ldots nl} \quad (3)$$

$$1 \leq i < j < \ldots < n \leq m;\ l = 1, \overline{C} \quad (4)$$

where $(\tilde{C}_{ij})$ is used to determine the degree of influence of each label on the linguistic values of attributes in the data, as shown in Equation (5):

$$D_l = \max_{1 \leq i < j < \ldots < n' < n} \left(\tilde{C}_{ij\ldots n'l}\right) + \min_{1 \leq i < j < \ldots < n' < n} \left(\tilde{C}_{ij\ldots n'l}\right) \quad (5)$$

The output label: Find the output label after applying the max operator using Equation (6):

$$\text{Output Label} = p \text{ if } D_p = \max_{l=1,C}(D_l) \quad (6)$$

Assign output labels and classify new samples: The final step in the FKGM model data processing is to classify new samples and assign the relevant output labels.

4. Illustrative Scenario-Based Implementation

In this section we introduce the data processing for the proposed FKGM model with an illustrative scenario-based numerical example. The scenario involves an automated window control system that adjusts the window's state (*fully open*, *half open*, or *closed*) based on environmental attributes such as *wind*, *light*, and *rain*, as discussed in Section 3.1. The objective is to determine the window's state using the predefined fuzzy rule base.

Inputs

Assume a set of fuzzy rules that encapsulate expert knowledge for controlling the smart window. The rules involve three input attributes, where the output labels define the window-opening state, where (1) equates to *fully open*, (2) equates to *half open*, and (3) equates to *closed*:

Wind: Low (1), Medium (1), High (1).
Light: Low (2), Medium (2), High (2).
Rain: None (3), Light (3), Heavy (3).

The output labels are defined as follows: the initial fuzzy rule base contains seven predefined rules for an existing example; these are presented in Table 2, where each rule includes linguistic conditions for *wind*, *light*, and *rain* as well as the output label.

We now turn to consider a new sample of data that does not exist in the predefined rules. For instance, suppose the sensor provides the following input values: *wind* = high (1), *light* = high (2), *rain* = heavy (3). This illustrative sample dataset does not directly appear in

Table 2. The task is to determine the output label to control the window system based on the fuzzy rule base in Table 2. To address the requirements, the following steps are carried out.

Table 2. Predefined fuzzy rules for window control system.

Rule	Wind	Light	Rain	Output
R1	High_1	Medium_2	Light_3	Closed (3)
R2	High_1	Low_2	Heavy_3	Closed (3)
R3	Medium_1	Low_2	Heavy_3	Closed (3)
R4	Low_1	High_2	None_3	Fully open (1)
R5	Medium_1	Low_2	None_3	Fully open (1)
R6	High_1	High_2	None_3	Half open (2)
R7	Low_1	High_2	Light_3	Half open (2)

Note: Subscripts 1, 2, and 3 denote the wind, light, and rain input attributes, respectively. Output values 1, 2, and 3 denote fully open, half open, and closed window states, respectively.

Step 1: Constructing the Fuzzy Knowledge Graph

We begin by representing the fuzzy rule base as an FKG. Each rule in Table 2 provides a semantic combination of the three input attributes along with the corresponding output label. There are seven rules, where each rule corresponds to a unique sample. The rules are processed as follows.

Consider Rule R1: Calculate $\left(A_{ij}^{t}\right)$ using Equation (4) as follows:

$$A_{12}^{1} = \frac{|\text{High1} \rightarrow \text{Medium2}|}{|R|} = \frac{1}{7},$$

$$A_{13}^{1} = \frac{|\text{High1} \rightarrow \text{Light3}|}{|R|} = \frac{1}{7},$$

$$A_{23}^{1} = \frac{|\text{Medium2} \rightarrow \text{Light3}|}{|R|} = \frac{1}{7}.$$

Next, using Equation (5) the weights $\left(B_{ij}^{1}\right)$ are calculated:

$$B_{1l}^{1} = \left(A_{12}^{1} + A_{13}^{1} + A_{23}^{1}\right) \cdot \frac{|\text{High}_1 \rightarrow \text{Closed}(3)|}{|R|} = \left(\frac{1}{7} + \frac{1}{7} + \frac{1}{7}\right) \cdot \frac{2}{7} = \frac{6}{7}.$$

Similarly, we compute $\left(B_{2l}^{1} = \frac{5}{36}\right)$ and $\left(B_{3l}^{1} = \frac{5}{18}\right)$. The results obtained for $\left(A_{ij}^{t}\right)$ from applying the six rules are shown in Table 3.

Table 3. Results of weight coefficients $\left(A_{ij}^{t}\right)$.

Rule	A_{12}^{t}	A_{13}^{t}	A_{23}^{t}
1	1/7	1/7	1/7
2	1/7	1/7	2/7
3	2/7	1/7	2/7
4	2/7	1/7	2/7
5	2/7	1/7	1/7
6	1/7	1/7	2/7
7	2/7	1/7	1/7

Note: A_{ij}^{t} denotes the edge-weight coefficient between input attributes i and j for rule t; indices 1, 2, and 3 represent wind, light, and rain, respectively.

The corresponding results for the weight coefficients $\left(B_{ij}^{t}\right)$ are shown in Table 4.

Step 2: Quick Reasoning Search Algorithm

To implement effective reasoning, a metaphorless simple algorithm based on the '*Rao algorithm*' [50], the *Fully Informed Search Algorithm* (FISA) [51], is employed. The FISA algorithm is used to assign labels to patterns that cannot be represented based on the rule base in the initial seven open rules. The reasoning mechanism of FISA is described as follows.

Table 4. Results of weight coefficients $\left(B_{ij}^{t}\right)$.

Rule	B_{11}^{t}	B_{21}^{t}	B_{31}^{t}
1	6/49	3/49	3/49
2	3/49	3/49	3/49
3	5/49	10/49	10/49
4	5/49	5/49	10/49
5	4/49	4/49	4/49
6	4/49	8/49	4/49
7	4/49	8/49	4/49

Note: B_{il}^{t} denotes the edge-weight coefficient connecting input attribute i to output label l for rule t; input indices 1, 2, and 3 represent wind, light, and rain, respectively.

Case 1: Assume that we assign labels to the first seven rules under the same condition as the seven initial open rules. This means that these rules are matched by the open rule base. Using Equation (6), we obtain (C_{il}) for each label (1) (1: *fully open*, 2: *half open*, or 3: *closed*). Consider R1, for $(l = 1)$ (*fully open*) we have

$$C_{11} = \sum_{t} B_{11}^{t} = 0,\ C_{21} = \sum_{t} B_{21}^{t} = 0,\ C_{31} = \sum_{t} B_{31}^{t} = 0.$$

Performing similar calculations, we obtain the following for $(l = 2)$ (*half open*) and $l = 3$ (*closed*):

$$\text{For } l = 2\ (\text{half open}): C_{12} = \frac{4}{49},\ C_{22} = 0,\ C_{32} = \frac{4}{49}.$$

$$\text{For } l = 3\ (\text{Closed}): C_{13} = \frac{4}{49},\ C_{23} = \frac{3}{49},\ C_{33} = \frac{3}{49}.$$

Then, using the min–max operator in Equation (6), we calculate (D_i) for each label where (1 = fully open, 2 = half open, 3 = closed). For example, consider Rule R1:

$$D_1 = \min(C_{11}, C_{21}, C_{31}) + \max(C_{11}, C_{21}, C_{31}) = 0$$

$$D_2 = \min(C_{12}, C_{22}, C_{32}) + \max(C_{12}, C_{22}, C_{32}) = \frac{4}{49} + 0 = \frac{4}{49} = 0.0816$$

$$D_3 = \min(C_{13}, C_{23}, C_{33}) + \max(C_{13}, C_{23}, C_{33}) = \frac{3}{49} + \frac{14}{49} = 0.3469$$

Given that $(D_3 > D_2 > D_1)$, according to Equation (6), the first label for rule $(R1)$ is (3: closed). By performing similar calculations, we obtain the first labels for rules $R2$, $R3$, $R4$, $R5$, $R6$, and $R7$ as follows: 3: closed, 3: closed, 1: fully open, 1: fully open, 2: half open, 2: half open, respectively. These results indicate that the labels derived from FISA match those obtained by directly checking against the corresponding rules in the rule base.

The inference coefficients for output label $l = 1$ (fully open) are shown in Table 5.

Table 5. Output label $l = 1$ (fully open).

Rule	C_{11}^t	C_{21}^t	C_{31}^t
1	0	0	0
2	0	4/49	0
3	4/49	4/49	0
4	5/49	5/49	18/49
5	4/49	4/49	18/49
6	0	5/49	18/49
7	5/49	5/49	0

Note: The first subscript identifies the input attribute (1: wind; 2: light; 3: rain), the second subscript identifies output label 1 (fully open), and superscript t identifies the rule.

The corresponding inference coefficients for output label $l = 2$ (half open) are shown in Table 6.

Table 6. Output label $l = 2$ (half open).

Rule	C_{12}^t	B_{22}^t	B_{32}^t
1	4/49	0	4/49
2	4/49	0	0
3	0	0	0
4	4/49	16/49	4/49
5	0	0	4/49
6	4/49	16/49	4/49
7	4/49	16/49	4/49

Note: The first subscript identifies the input attribute (1: wind; 2: light; 3: rain), the second subscript identifies output label 2 (half open), and superscript t identifies the rule.

The corresponding inference coefficients for output label $l = 3$ (closed) are shown in Table 7.

Table 7. Output label $l = 3$ (closed).

Rule	B_{13}^t	B_{23}^t	B_{33}^t
1	14/49	3/49	3/49
2	14/49	18/49	18/49
3	5/49	18/49	18/49
4	0	0	0
5	5/49	18/49	0
6	14/49	0	0
7	0	0	3/49

Note: The first subscript identifies the input attribute (1: wind; 2: light; 3: rain), the second subscript identifies output label 3 (closed), and superscript t identifies the rule.

Case 2: Given that we assign the first three labels = High1, Light = High2, Rain = Heavy3 (which do not belong to any of the seven open rules), we need to handle cases where existing rules cannot be directly applied. Specifically, in the FKG graph there is no connection from High1 to High2 or from High2 to Heavy3. However, separate paths still exist. Using the fuzzy inference mechanism FISA, the labelling process follows the principle shown below.

For Label 1 (fully open):

$$C_{\text{High1,1}} = 0,\ C_{\text{High2,1}} = \frac{5}{49},\ C_{\text{Heavy3,1}} = 0$$

$$D_1 = \min(C_{\text{High1,1}}, C_{\text{High2,1}}, C_{\text{Heavy3,1}}) + \max(C_{\text{High1,1}}, C_{\text{High2,1}}, C_{\text{Heavy3,1}})$$

$$D_1 = \frac{5}{49} = 0.1020$$

For Label 2 (half open):

$$C_{\text{High1,2}} = \frac{4}{49},\ C_{\text{High2,2}} = \frac{16}{49},\ C_{\text{Heavy3,2}} = 0$$

$$D_2 = \min(C_{\text{High1,2}}, C_{\text{High2,2}}, C_{\text{Heavy3,2}}) + \max(C_{\text{High1,2}}, C_{\text{High2,2}}, C_{\text{Heavy3,2}})$$

$$D_2 = \frac{16}{49} = 0.3265$$

For Label 3 (closed), given that $D_3 > D_2 > D_1$, the first label of this rule is 3 (closed):

$$C_{\text{High1,3}} = \frac{14}{49},\ C_{\text{High2,3}} = 0,\ C_{\text{Heavy3,3}} = \frac{18}{49}$$

$$D_3 = \min(C_{\text{High1,3}}, C_{\text{High2,3}}, C_{\text{Heavy3,3}}) + \max(C_{\text{High1,3}}, C_{\text{High2,3}}, C_{\text{Heavy3,3}})$$

$$D_3 = \frac{18}{49} = 0.3673$$

Since $D_3 > D_2 > D_1$, the first label of this rule is 3 (closed), as shown above.

5. Implementation

In this section we introduce the implementation for the FKGM model. To simulate the proposed model in a 'real-world' smart home environment, a range of sensors were used to collect 'real-time' data from multiple sources, including *temperature*, *humidity*, *light intensity*, *soil moisture*, and *rain*. Figure 3 shows the laboratory smart home model used to collect the sensor data and implement IoT-enabled monitoring control.

Figure 3. The laboratory smart home model used in the study; illustrating the process of operating smart home Internet of Things (IoT)-enabled monitoring control.

The hardware used to operate the window control system is shown in Figure 4.

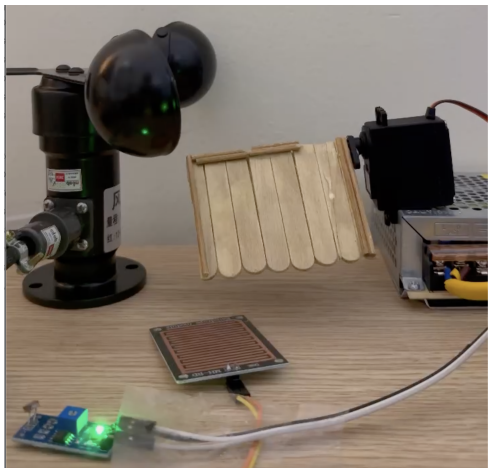

Figure 4. Hardware model; illustrating the process of operating the window control system.

The sensor technologies are addressed in Section 3, along with data collection. The sensor and data types used in the proposed FKGM control system are summarised in Table 8.

Table 8. The sensor and data types in the control system used in the proposed FKGM model.

Sensor	Type	Feature	Range	Unit	Processed Data	Output Decision
Light (sun)	Analogue Digital	Ambient light intensity	0–100	Lux level	Normalised value	Output label
Rain	Analogue Digital	Rain detection	0–100	%	Normalised value	Output label
Wind	Analogue Digital	Ambient wind level	0–100	%	Normalised value	Output label

Note: FKGM denotes Fuzzy Knowledge Graph Model. Sensor measurements are normalised to a 0–100 scale; the light-sensor range represents the normalised lux level, whereas the rain and wind ranges are expressed as percentages.

The FKGM model integrates the collected data into the FKG [52–54], processes the sensor inputs, and generates appropriate control actions. The output classification based on the resulting FKGM output labels is shown in Table 9.

Table 9. The output classification for the FKGM system based on the output labels.

Output	Output Label (Decision Result)
1	Fully open
2	Half open
3	Closed

5.1. Experimental Testing Hardware

To run the proposed FKGM model, Python 3 was used on a MacBook equipped with an M3 Pro chip. The MacBook M3 Pro, with its 12-core CPU, 18-core GPU, 16-core neural engine, and 16 GB of unified memory, provided sufficient computational power to run simulations and process large datasets. Additionally, a Raspberry Pi Pico W, programmed with MicroPython v1.27.0, was employed to interact with sensors and actuators in the real-world smart home environment. The Pi Pico W, with its dual-core ARM Cortex-M0+ processor, 264 KB SRAM, and built-in Wi-Fi, handled lightweight sensor data processing and device control within the smart home network.

5.2. Experimental Testing Smart Home

The proposed system supports access control through both mobile devices and personal computers, which can be operated as shown in Figure 5.

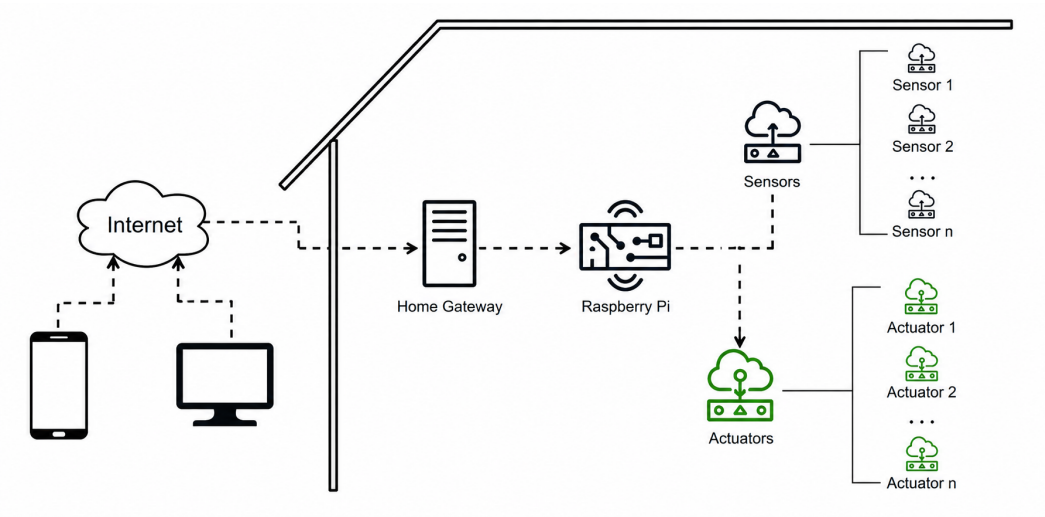

Figure 5. The smart home with Internet of Things (IoT)-enabled monitoring control.

Users can conveniently authenticate and interact with the smart home system through a simple interface, requiring only a single touch or command on their mobile device. From a system development perspective, mobile-based access control offers high implementation efficiency, excellent scalability, and ease of integration with Internet-of-Things (IoT) infrastructures. Consequently, it represents an effective and practical solution for modern smart home environments, improving both system security and the overall user experience. To access and control the smart home system through their web-based or app mobiles, user commands and configuration settings are transmitted to the home gateway, which serves as the primary communication gateway between the Internet and the home's internal network. Within the smart home environment, the Raspberry Pi functions as the central processing unit, collecting data from multiple sensors, including temperature, light intensity, rainfall, wind speed, soil moisture, and other environmental parameters. The collected data are subsequently processed using fuzzy reasoning techniques, such as fuzzy logic or a fuzzy knowledge graph (FKG), to infer the current environmental conditions and determine the most appropriate control actions.

The resulting control signals are transmitted to the corresponding actuators, including window control, lighting systems, ventilation fans, and other smart devices, enabling the system to interact directly with the physical environment. For example, the system can automatically adjust the window opening angle, regulate the brightness of lighting, and control the operating speed of ventilation fans according to the inferred environmental conditions. In addition, sensor measurements and the operational status of all connected devices are continuously transmitted back to the home gateway, which synchronises the information with the user interfaces. This enables users to monitor system status, configure operating parameters, and manage smart home devices in real time via web-based or app mobile interface.

In access-control mechanisms, the proposed approach significantly enhances accessibility, usability, and user convenience by enabling remote and real-time system access. Furthermore, it provides a cost-effective solution for secure identity management while simplifying system administration. By leveraging mobile computing technologies, users can seamlessly authenticate, monitor, and control smart home devices regardless of their location; the proposed smart home architecture provides flexible automation, robust decision making under uncertainty, and efficient real-time control. The incorporation of fuzzy

reasoning techniques further enhances the system's capability to process imprecise and uncertain sensor information, thereby improving the reliability, adaptability, and overall user experience of smart home management.

As compared to conventional fuzzy logic (FL) approaches, and the state of the art [55], the integration of the Fuzzy Knowledge Graph Model with the Fuzzy Inference System Algorithm (FISA) demonstrates several notable advantages in this study. Specifically, it provides a multi-dimensional knowledge representation framework, enables flexible reasoning under uncertainty, and exhibits greater adaptability to the complex and dynamic changes in the surrounding environment. By incorporating structured knowledge representation with fuzzy inference, the proposed model can effectively model intricate relationships among heterogeneous entities while maintaining robust decision-making capabilities in the presence of incomplete, imprecise, or uncertain data. Furthermore, the graph-based reasoning capability allows the smart home system to autonomously adapt the operation of connected devices in response to changing environmental conditions in the smart home.

5.3. Weighted Accuracy

To measure the accuracy of the control decisions, particularly when handling multi-level control actions (e.g., turning devices ON/OFF or adjusting intensity levels), the weighted accuracy method was used. This method accounts for the severity of errors made during decision making. Unlike binary output, which can be *correct* or *incorrect*, this approach assigns weights to different types of misclassification based on how far the system's decision deviates from the expected result.

For example, if a decision is expected to be "High" (level 3) but the system predicts "Medium" (level 2), the error is considered less severe than predicting "Off" (level 0). The formula for weighted accuracy (WA), predicted output (PO), and expected output (EO) is as shown in Equation (7):

$$\mathrm{WA} = 1 - \frac{\sum_{i=1}^{n} (|\mathrm{PO}_i - \mathrm{EO}_i| \times W_i)}{n} \tag{7}$$

where

$\boldsymbol{n}$: The total number of test cases (decisions).
$_{\boldsymbol{i}}$: The PO is the anticipated output result for the (i^{th}) test case.
$_{\boldsymbol{i}}$: The EO where the output is correct for the (i^{th}) test case.
$\boldsymbol{W_i}$: The weight assigned to the (i^{th}) test case (higher weights for larger deviations).
$|\mathbf{Predicted\ Output}_{\boldsymbol{i}} - \mathbf{Expected\ Output}_{\boldsymbol{i}}|$: Measures the deviation of the prediction from the expected result.

This method provides a more nuanced perspective on system performance as it distinguishes between mild and severe misclassification. In smart home control systems, where incorrect decisions can vary in impact, weighted accuracy is more relevant for performance evaluation.

6. Evaluation

To evaluate the performance of the proposed FKGM model we use four evaluation metrics: *accuracy* (see Equation (8)), *precision* (see Equation (9)), *recall* (see Equation (10)), and the *F1-score* (see Equation (11)). The four metrics are introduced in Section 6.1 (*accuracy*), Section 6.2 (*precision*), Section 6.3 (*recall*), and Section 6.4 (*F1-score*). The time is estimated by the total execution time of the system.

$$\mathrm{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{8}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{9}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{10}$$

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{11}$$

6.1. Accuracy

Accuracy is calculated as the ratio of the number of correctly classified samples to the total number of samples, as estimated by Equation (8), where

TP: The total number of true positive predictions; If $|\text{expected result} - \text{result}| = 0$.
TN: The total number of true negative predictions; If $|\text{expected result} - \text{result}| = 1$.
FP: The total number of false positive predictions—when the expected result is fully open but the control result is closed.
FN: The total number of false negative predictions—when the expected result is closed but the control result is fully open.

6.2. Precision

To evaluate the accuracy when the system predicts a *positive* label, the *precision* metric is used, as shown in Equation (9), where

TP: The total number of true positive predictions; If $|\text{expected result} - \text{result}| = 0$.
FP: The total number of false positive predictions—when the expected result is fully open but the control result is closed.

A high precision score indicates that the system makes fewer false positive predictions, thus reducing the occurrence of "false alarms". In the context of smart home control, minimising false positive predictions helps avoid unnecessary control actions (e.g., opening/closing windows at the wrong time).

6.3. Recall

Recall measures the system's ability to identify all "positive" cases, as shown in Equation (10), where

TP: The total number of true positive predictions; If $|\text{expected result} - \text{result}| = 0$.
FN: The total number of false negative predictions—when the expected result is closed but the control result is fully open.

A high recall score indicates that the system misses fewer important cases. In the context of smart home applications, this ensures that the system detects all abnormal situations (such as heavy rain or strong winds) to make timely control decisions.

6.4. F1-Score

The F1-score is the harmonic mean between precision and recall, as shown in Equation (11). The F1-score reflects the balance between precision and recall. A system with a high F1-score indicates both good positive prediction accuracy (i.e., fewer false positives) and coverage of most positive cases (i.e., fewer false negatives).

7. Results

So far, we have introduced the FKGM model along with the implementation and evaluation strategy and provided an introduction to the fuzzy logic rules along with the methodology. In this section we set out the simulated results based on 27 test cases, where

the results of the evaluation metrics, including the calculated results with respect to *accuracy*, *precision*, *recall*, and the *F1-score*, are as follows:

Accuracy:

$$\text{Accuracy} = \frac{18+8}{27} \approx 0.96296\ (\approx 96.3\%)$$

Precision:

$$\text{Precision} = \frac{18}{18+1} = \frac{18}{19} \approx 0.9474\ (\approx 94.74\%)$$

Recall:

$$\text{Recall} = \frac{18}{18+0} = 1.00\ (100\%)$$

F1-score:

$$\text{F1-score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = \frac{2 \times 0.9474 \times 1.00}{0.9474 + 1.00} = 0.973\ (\approx 97.3\%)$$

The results indicate that the FKGM model achieves high accuracy levels and provides an effective basis to realise full recognition (*recall* = 100%), with low false positives (precision = 94.74%) leading to a high F1-score. This is evidence of the overall effectiveness of the FKGM system. For our reported results we also consider the following:

Execution time: Turning to the *execution time*, the execution time for the entire inference and evaluation process is measured by taking the difference between the start and end times of the program. The result shows an execution time of approximately 0.00039 s. This demonstrates the efficiency or the proposed model.

Distribution of output labels: The experimental testing was based on 27 samples. The system's predictions are concentrated mainly in output labels 1 and 3, with fewer predictions for output label 2. However, the overall accuracy remains very high.

The distribution of samples classified as true positive, true negative, and false positive is shown in Figure 6.

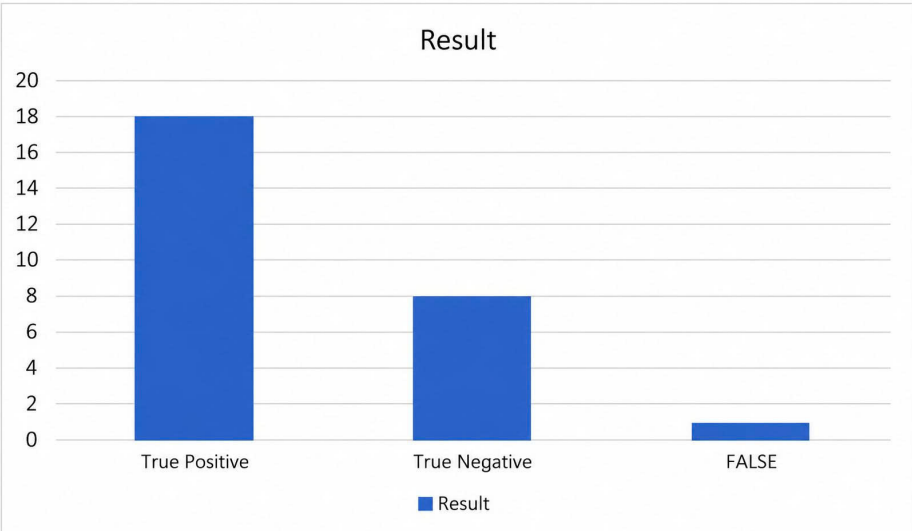

Figure 6. Bar chart showing the number of samples predicted as being in the true positive, true negative, and false positive categories. Each bar represents the number of times the system classified samples into the corresponding group, showing that most predictions belonged to the true positive group, fewer fell into the true negative group, and very few were incorrect.

The expected output-label distribution for the *fully open*, *half open*, and *closed* states is shown in Figure 7.

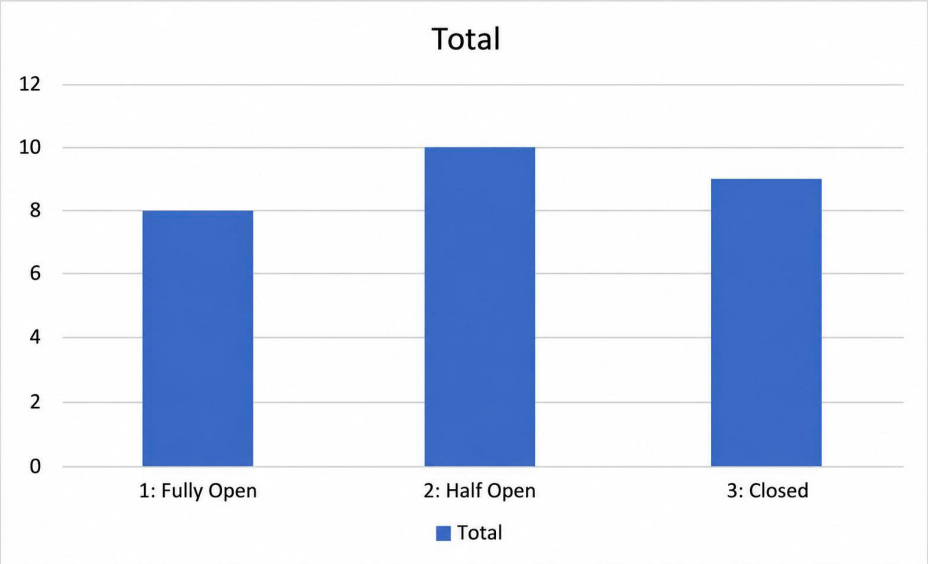

Figure 7. Bar chart showing the number of samples predicted, with the expected values for the output labels *fully open*, *half open*, and *closed*.

The corresponding distribution of the actual predicted output labels is shown in Figure 8.

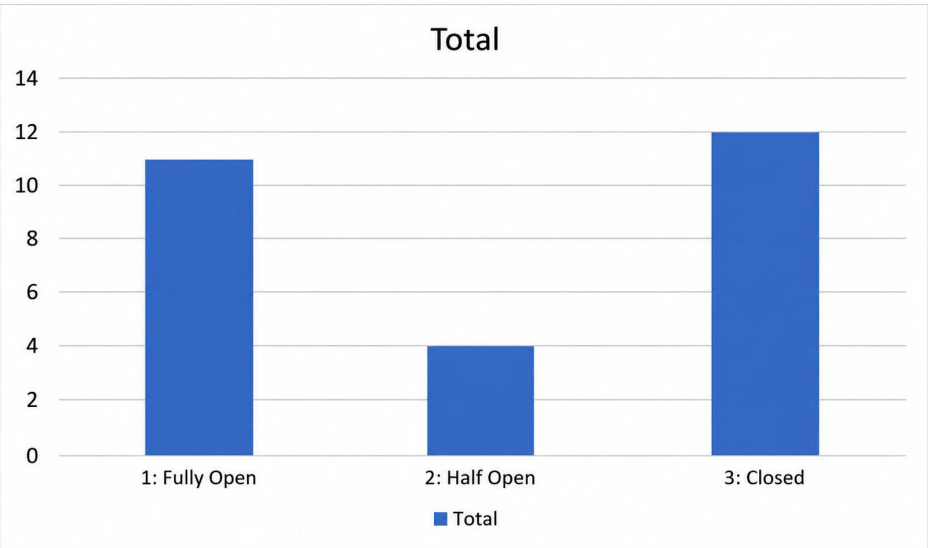

Figure 8. Bar chart showing the number of samples predicted, with the actual results for the output labels *fully open*, *half open*, and *closed*.

The smart home device and sensor monitoring interface used to display the system status is shown in Figure 9.

These results confirm the effectiveness of the model in making window open/close decisions based on input information (wind, sunlight, rain) with high reliability. Comparing the research in [56] [which uses traditional fuzzy logic in smart home control, focusing on energy storage systems], the FKGM model combined with the FISA algorithm demonstrates advantages in its ability to represent multi-dimensional knowledge, handle uncertain data flexibly, and adapt better to complex environmental variations. On the other hand, while

traditional fuzzy logic solutions are easy to implement and suitable for specialised tasks such as energy control, they face challenges when it comes to scaling and managing knowledge in cases where data becomes complex and incomplete.

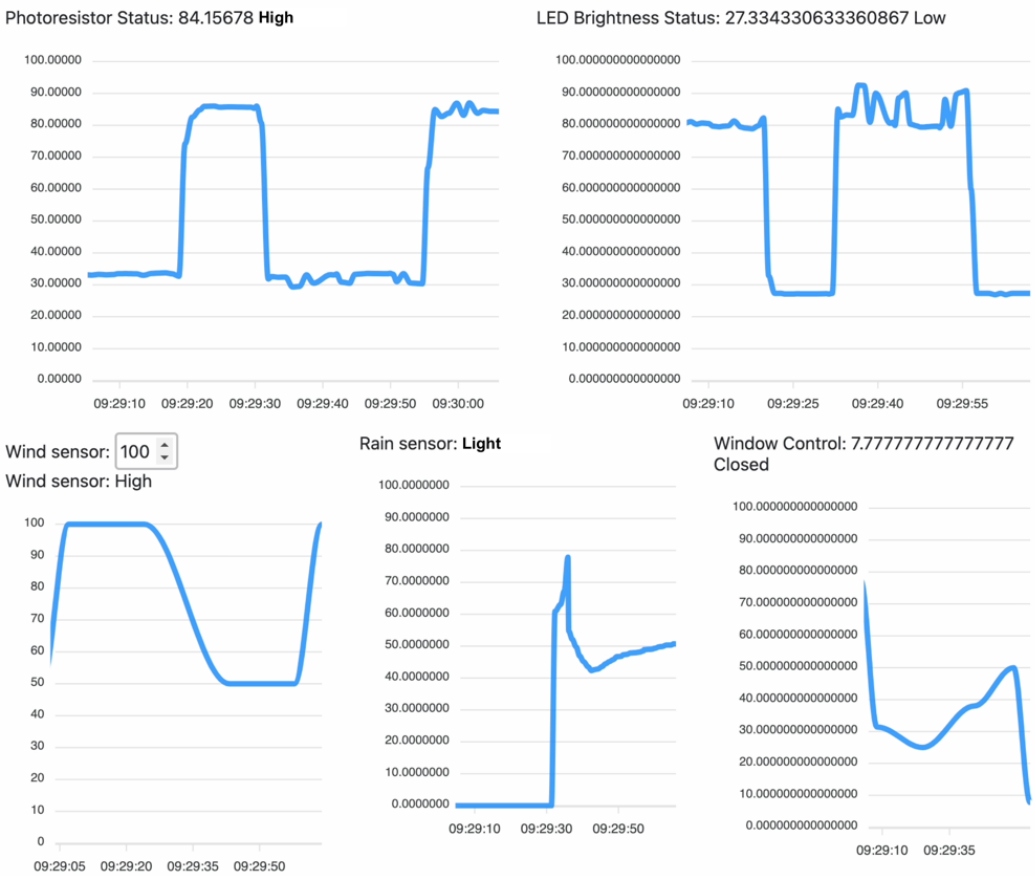

Figure 9. Smart home device and sensor monitoring interface.

Moreover, when compared to the rule-based and context-based automated control method introduced in [57], which is a simple, intuitive, and effective solution in less dynamic environments, the FKGM model combined with the FISA algorithm proves to be superior due to its ability to process fuzzy and uncertain data without requiring the creation of specific rules for every scenario. It easily extends knowledge to minimise the need for re-defining numerous rules when the environment or control requirements change, while still ensuring high accuracy and fast response times to effectively meet the demands of real-time applications.

Comparing the FKGM model combined with the FISA algorithm to the context-aware rule-based automated control method introduced in [57], we can observe the following:

- While the method introduced in [57] is a relatively simple intuitive and effective solution in less dynamic environments, the proposed FKGM model can be seen to be superior due to its ability to process fuzzy and uncertain data without requiring the creation of specific rules for every scenario.
- The proposed FKGM model easily extends knowledge to minimise the need for re-defining numerous rules when the environment or control requirements change, while still ensuring high accuracy and fast response times to effectively meet the demands of real-time applications.

8. Discussion

As discussed in Section 1, healthcare provision represents a multi-factorial challenge, where a significant issue is the inherent uncertainty in the data, which forms the fundamental focus of this study. However, the focus of this study and article is on the processing of data derived from a smart environment. Accordingly, in this article we have introduced our novel FKGM model, which utilises FKG technology. We posit that our proposed model provides numerous significant advantages that importantly include the management and processing of data that is uncertain, lacks precision, and may be ambiguous. Addressing this challenge lies at the heart of our research, which has resulted in a number of contributions, which we have set out in Section 1.

As discussed in this paper, a KG is made context-aware by a collection of interlinked descriptions of concepts, entities, relationships, and events; this provides a framework for data integration, unification, analysis, and data sharing. The Resource Description Framework (RDF: https://www.w3.org/RDF/ (accessed on 30 July 2026)) (RDF) is a graph-based data model which provides an interesting framework to represent data and metadata. RDF is a *Semantic Web Standard* for describing resources and data interchange. RDF is developed, updated, and standardised by the World Wide Web Consortium (W3C: https://www.w3.org/ (accessed on 30 July 2026)) (W3C). RDF has influenced the KG concept and knowledge models, which form a critical component in this research and in the development of our FKGM model.

The FKG method enables the system to represent knowledge flexibly and multi-dimensionally, leading to more accurate decisions when the collected data is fuzzy, incomplete, or unstable. The reasoning capability of the FKG allows smart environments to automatically adjust devices in response to environmental changes, improving operational efficiency and user experience. In Section 2, we considered related research addressing KGs, FKGs, and related fuzzy systems as they relate to this study.

As identified in Section 2, the use of KGs, FKGs, and fuzzy systems has been shown to provide significant levels of utility. A KG is an important component in a knowledge model, which is a collection of interlinked descriptions of concepts, entities, relationships, and events. The integration of an FKG into an intelligent context-aware monitoring system offers numerous outstanding advantages, particularly in handling uncertain and ambiguous data, which we exploit in the development of the proposed FKGM model.

In the evaluation of the proposed FKGM model, the reported results (see Section 7) show that the proposed model achieves good statistically significant results in terms of accuracy (recall: 100% with low false positives; precision: 94.74%), leading to an F1-score of 97.3%. These metrics demonstrate the effectiveness of the proposed model along with its ability to fully identify situations requiring intervention in decision-support systems. Moreover, the evaluation confirms the reliability, stability, efficacy, and utility of our proposed model. Moreover, implementation on a standard commercial laptop computer demonstrates the benefit gained from low computational overhead with a rapid response time, which is an important consideration supporting the claim that the FKGM method has significant utility and is capable of responding rapidly in 'real time' in smart environments.

However, when considering 'real-world' implementation, we must carefully weigh the exceptional benefits of FKG (handling complex fuzzy data, high predictive performance) against resource costs, development complexity, and expertise requirements. This ensures stability, scalability, and practical deployment effectiveness for smart home applications in the long term. Additionally, there will be potential socio-technical and ethical issues [58], which need careful consideration. Such issues are beyond the scope of this article and in practice are the subject of a specific research field(s). Notwithstanding, the research ad-

dressing the potential and developing socio-technical and ethical issues must be considered in terms of information systems' design and implementation [59].

8.1. Open Research Questions and Potential Directions for Research

While this research has addressed our primary research goal, which in summary relates to data management and processing under dynamic uncertainty in intelligent context-aware monitoring systems, there remain challenges, including the following:

Noisy data: As we have discussed in Section 1, sensor-derived raw data can typically be imprecise, inaccurate, and/or incomplete [often characterised as 'noisy data'], which can present a significant issue. As this relates to the FKGM model, future research will focus on expanding the model capability and the integration of additional data source devices to improve: (a) the ability to generalise to diverse domains of interest in more complex scenarios, and (b) the performance in diverse scenarios. These improvements are expected to enhance FKGM's role in building flexible, efficient, and highly reliable smart home systems.

Implementation and fuzzy theory: Implementing an FKGM model requires in-depth expertise in both fuzzy theory and knowledge representation. This is reflected in the need for a collaborative team-based approach where computer scientists (with limited or no medical expertise) work with clinicians (with limited or no computing expertise). This makes the process of building and maintaining the system complex. A potential solution may lie in developing a cloud-based systems such as software-as-a-service (SaaS), networking-as-a-service (NaaS), or infrastructure-as-a-service (IaaS).

Knowledge management: Expanding or updating knowledge in the continuously evolving context of smart environments represents a significant challenge. Moreover, hardware devices with limited computational capacity may have issues when data processing aims to perform reasoning [60] on the fuzzy knowledge graph. As with the SaaS, NaaS, and IaaS approaches, a potential solution may be to implement sensor data preprocessing in a cloud-based system, as discussed in Section 1.

Benefits: While our proposed system achieves significant results in terms of *accuracy*, *recall*. *F1-score*, and *response time*, implementation must consider the benefits (handling complex fuzzy data, high predictive performance) against the resource costs, development complexity, and expertise requirements. Such consideration is required to ensure stability, scalability, and generalisability in terms of practical deployment effectiveness [as briefly addressed in Section 8.2] in the long term in a diverse range of domains of interest.

Security: As with all data-intensive applications, there will be security and ethical concerns; these are beyond the scope of this paper. Such concerns represent specific research fields but these considerations must form an important element in systems design and implementation.

8.2. Practical Managerial Significance

Considered from a practical managerial significance perspective, the FKGM model has been shown to run effectively on a MacBook M3 Pro with integration on Raspberry Pi Pico W hardware using MicroPython v1.27.0. The evaluation and analysis demonstrates the ability of the proposed model to operate effectively in 'real time' in 'real-world' environments using "low-powered" computer systems, where there is a need for flexibility of approach under various deployment conditions.

Moreover, we posit that the proposed FKGM model will generalise to a diverse range of domains of interest given that semantic representation [as discussed in Section 3.1] can be applied with a domain-specific nature, as in the use of semantic terms used in "concept learning", as discussed in [43], where the potential benefits derived from the use of this approach have been demonstrated and validated in practical 'real-world' examples.

9. Concluding Observations

In this paper we have introduced our proposed novel FKGM model, which is predicated on FKG technology and has been conceived and developed to address data processing in dynamically complex and uncertain smart environments.

The implementation process, including data preparation, reasoning, and action control, has been validated through experimental testing. The reported results indicate that the model not only maintains high levels of accuracy, with good precision, recall, and F1-score, but the results also confirm the reliability, stability, and utility of our proposed method.

Source code: Smart home FKG source code is available at https://github.com/datalake-ekg/smarthome (accessed on 30 July 2026).

Author Contributions: Conceptualisation and methodology: P.S., H.V.P. and P.M.; software: P.S. and H.V.P.; validation: H.V.P., F.A. and P.M.; formal analysis: P.S., T.Q.N. and H.V.P.; investigation: P.S. and H.V.P.; data: T.Q.N. and F.A.; writing—original draft preparation: F.A. and H.V.P.; writing—review and editing: P.S., T.Q.N., H.V.P. and P.M.; project administration: H.V.P. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data used in this study are publicly available in benchmark datasets as stated in the paper.

Conflicts of Interest: The authors declare no conflicts of interest. The funder had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results. In this study no Generative AI systems [which include MS Copilot and similar systems] have been used for any purpose in conducting this study with respect to research activity, literature review, and manuscript preparation. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

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