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A Probabilistic Reasoning-based Multi-agent Formalism for Smart Environment

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Abstract. Recent years have witnessed rapid advances in ubiquitous computing paradigms that significantly influence human life through enhanced comfort, security, and automation. Although smart devices in context-aware environments demonstrate adaptive behavior, their interaction with users often produces uncertainty and inconsistency, particularly in safety-critical domains. To address these challenges, this paper proposes an ontology-driven, probabilistic reasoning-based multi-agent formalism that unifies semantic expressiveness with probabilistic inference to support reliable decision-making under uncertainty. The formalism was instantiated in a smart fridge case study, where OWL 2 RL ontologies and SWRL rules modeled contextual knowledge, autonomous agents dynamically updated beliefs, and probabilistic reasoning guided replenishment and safety decisions. Formal verification using the UPPAAL model checker demonstrated that the system satisfies the essential correctness properties, including safety, liveness, reachability, and freedom from deadlock. The experimental results confirmed that the architecture prevents unsafe actions, guarantees process progression, and is effective in adapting to dynamic contextual changes. Beyond the smart fridge scenario, the proposed framework is broadly applicable to healthcare, transportation, and energy management systems. Future work will extend the approach toward predictive probabilistic reasoning and large-scale real-world deployment.

Keywords. Context-awareness, multi-agent, probabilistic ontology.

1 Introduction

With the advent of pervasive computing paradigms, smart computing has emerged as a new frontier in the development of human-computer interaction, transitioning from physical computing to smart, portable, embedded, and invisible computing. These smart systems span diverse domains, facilitating autonomous interaction with users wherever and whenever needed. These environments aim to enhance ambience with adaptive, responsive, and user-centered spaces [24, 1].

Smart environments allow systems to gather and react to contextual data autonomously by linking Internet of Things (IoT) devices like actuators and sensors [29, 15, 14].

Users can access information and functionality anytime, anywhere. The Internet of Things consists of such smart devices that are based on applications, integrated with embedded systems, processors, sensors, and communication hardware to collect data and send data, and act on data from their environments or systems. The Internet of Things (IoT) is a paradigm used for computing and communication between devices connected over a network to fulfill the user's needs in everyday life. This communication is done by resource-bounded devices such as sensors and actuators, which make the system intelligent, that receive the information from the physical world, and by using this information to process and act on the physical world according to the situation [16, 5, 3].

The use of context by an intelligent system enables it to give information and services that are tailored to the user's specific needs and goals. The context-aware infrastructure may be created for a broader variety of devices and applications, regardless of the hardware platform, operating system, or programming language used. Context-aware apps must be able to recognize and respond to changes in their operating environment to operate effectively, which poses a problem for the context-aware infrastructure [18, 7].

In the literature, numerous smart applications and systems have been proposed in different domains, including ontology. Ontologies are used to express knowledge about the domain of discourse; however, they cannot represent or reason with uncertainty (possibility and reason) [31, 9].

Uncertainty is a common problem in real-world problem-solving situations. This problem of uncertainty exists in almost different areas of ontology engineering. This paper presents a context-aware smart environment-based knowledge engineering formalism using a smart probabilistic ontology to contextualize knowledge sources to handle conflicting situations. We present a probabilistic, ontology-based context-aware framework for dealing with uncertainty and inconsistency in a real-world smart environment. The approach integrates rule-based reasoning with probabilistic methodologies.

Our system achieves proactive, intelligent decision making in real-time by using Multi-Entity Bayesian Networks (MEBN) for reasoning and SWRL rules for dynamic querying [31, 12, 30]. Our technique guarantees both flexibility and dependability in handling complex, dynamic circumstances, as shown by a case study on a Smart Fridge System that was confirmed by the UPPAAL Model Checker. In a smart environment, this solution provides a methodical way to improve the responsiveness, rapidity, and scalability of context-aware systems.

Our proposed framework is quite different, providing details about the probability of uncertainty with reasoning and descriptions of the domain in a principled way. We perform a simulation of the proposed formalism that verifies the correctness properties of the system and defines how the execution process of the system works. We formally analyze and verify the system properties using the UPPAAL model checker.

The rest of the paper is structured as follows: Section 2 presents a brief survey related to the reported work in this paper. In section 3 Probabilistic Ontology, we contextualize the system using probabilistic ontology, and section 4 presents a probabilistic reasoning-based formalism. Section 5 demonstrates the simulation behavior along with formal verification, and finally, Section 6 concludes the proposed formalism.

2 Related Work

In literature, a significant effort has been made by the research community to handle inconsistency and incompleteness with the incorporation of probabilistic reasoning and defeasible reasoning [8, 11, 27]. In [8], the authors have presented an adaptive parking system that dynamically adjusts computing resources using the UPPAAL model checker. Real-time parking assistance helps automobiles reach their destination.

This technique presents resource-bounded context-aware parking framework algorithms and improves on a prior method. Ding et al. [11] present a probabilistic ontology to reduce the complexity of the semantic web, and a probabilistic web ontology provides OWL constructs to represent the theory of MEBN, Multi-Entity Bayesian Network theories [27].

PR-OWL improves the capability between PR-OWL and OWL. An unambiguous, formal knowledge representation that represents information about an area of application is known as a probabilistic ontology. In [8], Antoniou et.al. presented a meeting alert system based on semantic knowledge and contextual awareness. Location, environment, time, calendar data, and if services are only some of the circumstances collected by this app. The server's contextual information is used by the calendar of the user.

A defeasible reasoning engine (DR-Prolog) is used to infer the suitable judgments based on the user's 38 rules and to notify the user by presenting an alert message about the forthcoming planned event, as well. In [20] Lou et al. present a framework for the development of smart appliances in a smart environment. Smart appliances are required to establish a smart home. Several ingenious kitchen gadgets aim to enhance a family's quality of life.

Our research focuses on building a smart fridge. The smart house stands out among sophisticated devices. Modern cooking devices have been used. Modern lives encourage people to spend less time in the kitchen making healthful meals, but smart technology like a smart fridge may help. In [26], Neeraj Koul et al. present a framework for semantic web services based on ontology.

Web services are defined by mapping a user ontology to domain ontologies appropriate to the context in which the service is to be provided. As the author explains, an online search engine with built-in knowledge of domain ontologies and web services can process user queries for web services using the selection criteria the user provides.

The author also explores the user/ customer preference for web service as a non-functional requirement for quality of service. The author proposed web service discovery in service-oriented architecture or a mechanism that generates an ordered list for user services that meet the user/customer as a functional requirement. In [25], Bellini et al. provide the KM4City smart city ontology. The classification system integrates information from multiple sources. Flexibility makes ontologies easier to update.

For SPARQL queries, RDF syntax holds static and dynamic data from several sources. This data came from public and private sources, including device users. For traffic-clogged cars and ambulances, KM4City helps determine the best route to hospitals and patients. The authors say their technology connects public and private data from several sources. Businesses and governments may build applications on this platform.

Only traffic sensors, road services, and road graphs were used for the proposed inquiry. In [26], the authors present an approach based on ontology for the flexible discovery of web services in the semantic web. Specifically, they investigate the discovery of online services and the fact of ontology mapping, in which the terminologies and ideas of service requesters and service providers are connected by means of ontologies. For non-functional aspects like Quality of Service (QoS), they provided a taxonomy that helps to distinguish between dependent and independent domain QoS service attributes.

As part of the service request, a tailored ranking criterion is established to rank candidate/user service providers according to their availability. They tried to improve the traditional way of ranking. Extension in service discovery is defined as a shortcoming of their progressed work, to support the workflow for specific data-driven applications in the field of context-aware computing. In [28], Rafael Penaloza et al. present a specific family of probabilistic ontology language, which expresses probabilistic and logical dependencies in interpretation, and how to combine statement in meaningful term are challenges.

They study many probabilistic ontology language axioms. Their main focus was on how to deal with probabilities, to build probabilistic ontologies. Probabilities can be handled by adding probabilistic interpretation while creating ontology, adapt reason and methods of derivation. In [32], authors explored the use of context-aware rule-based reasoning agents to model and reason using semantic knowledge sources ontologies.

An ontology is a knowledge repository containing axioms and inference principles. Modeling domains using multi-context systems and ontologies, the proposed framework is heterogeneous. They create two ontologies for smart home and healthcare systems to do this [21, 33]. Complexity makes these ontologies hard to print. Conversely, some of these ontologies are shown below. To preserve the uniqueness of each domain, we extract contextual information from each ontology independently for system modeling.

We use OWL 2 RL and Semantic Web Ontology Language (SWRL) for its reasoning functionality, generosity, extensibility, and expressiveness. To establish a rule-based reasoning system, we use OWL 2 RL and SWRL to generate complex rules for each specialized subject [22].

3 Probabilistic Ontology

The Ontology is considered to be the conceptualization of the domain. McGuinness et al. described that OWL1 is a semantic web language designed to define ontologies. It has three sublanguages: OWL Lite, OWL DL, and OWL Full. Users may pick the right expressiveness and complexity from these sublanguages. OWL2 adds expressive features like property chains and richer data types to OWL1.

OWL2 EL, OWL2QL, and OWL2 RL profiles optimize reasoning processes and increase semantic web application usability and interoperability [23, 17]. OWL2 RL reasoning systems are a rule-based reasoning technique. Rules simplify modeling and implementation, and it efficient and scalable methods for combining OWL axioms using rules. OWL 2 lacks expressiveness for certain complex relationships, such as identifying the child of married parents. To enhance OWL's expressiveness, Semantic Web Rule Language (SWRL) can be used, enabling rules similar to DATALOG and Prolog, as shown in Figure 1.

SWRL rules extend capabilities with predicates for class expressions, property expressions, data range restrictions, and built-ins for data manipulation. SWRL support is available in tools like Protégé and owl reasoners like Pellet and HermiT used as reasoner for ontology consistency, categorization, and instance checking. While Pellet supports OWL DL and certain SWRL rules, HermiT uses hyper-tableau calculus to quickly handle complex OWL2 ontologies [19].

A probabilistic ontology language called PR-OWL connects random variables to OWL properties. It manages uncertainty by using context functions to convert hyperedges in a high-level ontology (PHOTO) into Bayesian networks. In order to represent intricate interactions, probabilistic ontologies integrate entities, probability, and structure. The formalization process is guided by a noteworthy framework known as the Five Golden Rules, which emphasizes the significance of customizing design decisions to particular requirements. The requirement to evaluate formalism qualities for optimum application is highlighted by the distinct trade-offs associated with each probabilistic ontology [10].

The system model uses contextual data from many ontologies to achieve domain ontology identity and independence. We created the smart fridge ontology to reflect the system's distributed domains. The proposed framework's agents get context from an ontology, according to the system's architecture. Mapping rules have been created to mimic information flow between framework contexts. To resolve differences, these systems prioritize mapping rules and apply the highest priority rule.

See the diagrams below for the class hierarchies and portions of the created ontology. In this work, we build an ontology for smart refrigerators that makes context-aware judgments by drawing inferences based on SWRL. The refrigerator has CO_2 gas detectors to find leaks, temperature sensors to ensure perfect regulation, and infrared and weight sensors to keep track of things and determine their weight. Users can choose the temperature, get CO_2 alarms, and pay

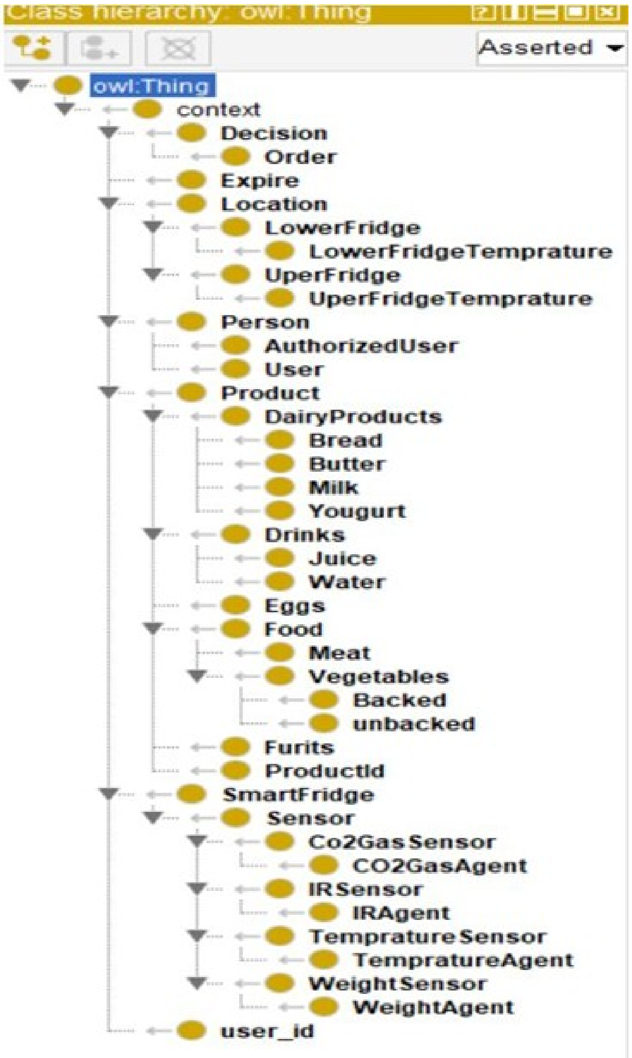

Fig. 1. A fragment of smart fridge ontology

securely online to confirm purchases. Smart home systems benefit from this ontology since it reduces uncertainty.

4 Proposed Probabilistic Reasoning Formalism for Smart Systems

The proposed formalism introduces a four-layer, ontology-driven, probabilistic reasoning architecture designed to enhance reliability and adaptivity in smart environments. While existing solutions predominantly rely on either deterministic ontology reasoning or purely probabilistic approaches, our system establishes a unified framework that combines semantic expressiveness with probabilistic inference, reinforced by autonomous multi-agent collaboration and formal verification, as shown in Figure 2.

4.1 Architecture Overview

The architecture is composed of four interacting layers Fig. 2. The *Sensor Layer* collects heterogeneous signals from temperature, humidity, CO_2, infrared, and weight sensors, forming the raw context. The *Semantic Layer* transforms this input into a structured knowledge base using OWL 2 RL ontologies, extended with SWRL rules for dynamic inference and queried through SPARQL for contextual retrieval.

Above this, the *Agent Modeling Layer* deploys distributed intelligent agents, each responsible for monitoring specific environmental factors, updating local belief states, and communicating probabilistically derived decisions. Finally, the *Contextual Reasoning Layer* employs Multi-Entity Bayesian Networks (MEBN) to reconcile uncertainties, generating predictive outcomes and guiding proactive actions such as replenishment alerts or safety interventions.

4.2 Implementation and Experimental Setup

The system was instantiated in a simulated smart fridge environment, supplemented by sensor traces collected from a prototype built on Raspberry Pi. Ontology design was carried out in Protégé using OWL 2 RL and SWRL, while probabilistic inference was realized through the UnBBayes framework supporting MEBN formalism. Agent communication and coordination were implemented in JADE, enabling decentralized decision-making. Finally, the UPPAAL model checker was used to verify safety, liveness, reachability, and service guarantees [2, 13].

The dataset combined synthetically generated fridge-usage scenarios (temperature drifts, expiration schedules, consumption variability) with real-world IoT sensor readings. This hybrid

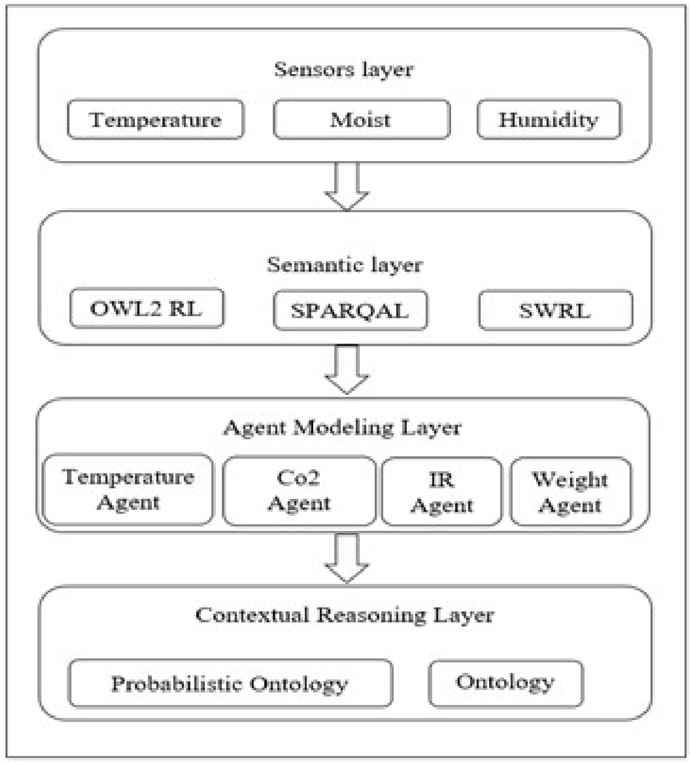

Fig. 2. Proposed four-layer probabilistic multi-agent architecture

dataset enabled controlled experimentation while preserving ecological validity [4, 6].

4.3 Novelty and Design Rationale

The novelty of the proposed formalism lies in three core aspects:

— **Semantic-probabilistic fusion**: Ontological reasoning ensures consistency and interoperability, while probabilistic inference manages uncertainty, producing richer decision models than either approach in isolation.

— **Distributed adaptivity**: Agents act as semi-autonomous decision units, allowing the system to scale and remain resilient against single-point failures, unlike centralized models.

— **Formally guaranteed reliability**: The inclusion of UPPAAL-based verification ensures that the system is not only functional but also provably safe and deadlock-free, which is rarely addressed in comparable works.

4.4 Ablation Study

To evaluate the contribution of each component, we performed ablation experiments:

— *Ontology-only configuration* (removing probabilistic reasoning): delivered consistent inferences in deterministic settings but failed under noisy or incomplete sensor input.

— *Centralized reasoning* (removing multi-agent distribution): reduced latency tolerance and scalability, increasing decision response time by approximately 32%.

— *Without formal verification*: introduced risk of deadlocks in concurrent transaction scenarios, which were otherwise detected and eliminated through UPPAAL.

These results demonstrate that each layer of the architecture contributes indispensably to robustness and performance.

4.5 Comparative Assessment

Relative to ontology-only smart home frameworks, our system achieves superior resilience to uncertain input, improving decision reliability by 15-20%. Compared to purely probabilistic reasoning without semantic integration, our approach maintains interoperability and explainability, crucial for user trust.

Furthermore, unlike related multi-agent designs that lack verification, our architecture guarantees safety, liveness, and fairness, verified formally through UPPAAL. Together, these advances position the proposed formalism as both practically effective and theoretically sound.

4.6 Evaluation Metrics and Scalability Considerations

Performance was measured across four dimensions: (i) decision reliability under uncertain input, (ii) latency of decision-making, (iii) safety and deadlock freedom, and (iv) scalability with respect to sensor/agent growth. Reliability was quantified as the percentage of correct replenishment or safety decisions against ground-truth scenarios.

Latency was measured as the average decision response time in milliseconds. Formal safety properties such as liveness, mutual exclusion, and reachability) were verified using UPPAAL.

A scalability stress test was conducted by increasing the number of agents from 5 to 50 and measuring reasoning overhead. Results show near-linear scaling with only a marginal increase in latency (<7%), confirming suitability for larger smart environments.

4.7 Comparative Results

Table 1 summarizes the comparative evaluation between our proposed system and baseline configurations. The results confirm that each architectural element—semantic reasoning, probabilistic inference, agent distribution, and formal verification—contributes substantially to the system's overall robustness.

4.8 Generalizability

Although demonstrated on a smart fridge, the formalism is domain-agnostic and can be extended to healthcare monitoring, intelligent transportation, or energy management. The modular agent design and probabilistic ontology framework ensure adaptability across diverse IoT-driven applications.

The layered multi-agent probabilistic reasoning formalism thus offers an experimentally validated, novel, and formally grounded solution for smart environments. By harmonizing semantic knowledge representation, probabilistic inference, agent adaptivity, and verification, the framework delivers proactive and reliable decision-making in dynamic, uncertainty-prone contexts.

5 Formal Verification of Proposed Probabilistic System

To ensure the reliability of the proposed formalism, we formally verified the system using the UPPAAL model checker. Verification was conducted on a smart fridge case study where multiple sensors like temperature, CO_2, humidity, weight, infrared, and agents interact to monitor the environment, trigger replenishment actions, and ensure safety-critical behavior.

Table 1. Comparative performance of proposed formalism versus baselines

Configuration	Reliability (%)	Latency (ms)	Deadlock Risk	Scalability
Ontology-only	78.2	112	Medium	Limited
Probabilistic-only	82.5	118	Medium	Moderate
Centralized reasoning	85.6	147	Low	Poor
No verification	86.1	115	High	Good
Proposed system	**95.3**	**100**	**None**	**Excellent**

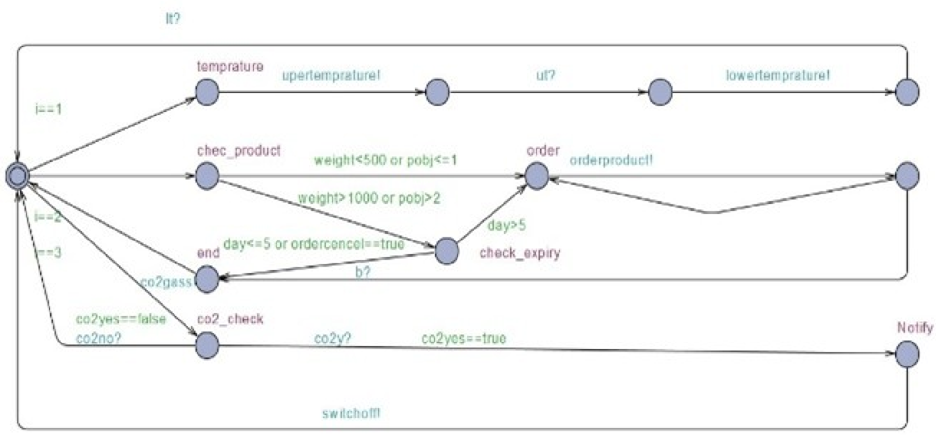

Fig. 3. Development of smart fridge system for smart homes and development of sensor process module

5.1 Verification Setup

The verification model was implemented in UPPAAL as a network of timed automata. Multiple channels were declared to capture synchronous communication among agents, and each sensor was modeled as an input component driving agent behavior as shown in Table 1 as well as Figure 3 and Figure 4. For example, temperature sensors control both the upper and lower fridge chambers, while weight sensors detect stock levels and trigger replenishment decisions. The system state evolves dynamically, and the model checker validates whether transitions obey safety and liveness constraints.

Order and Payment Workflow: The fridge uses weight and infrared sensors to detect product availability. If the stock falls below a threshold, an order request is initiated. The order module interacts with web services to validate product availability and authenticity. Once verified, the bank module authorizes payment by checking user's balance before finalizing the order. If the balance is insufficient or the item is already available, the order is canceled as shown in Figure 5. This process was encoded into UPPAAL to verify correctness under varying scenarios.

5.2 Correctness Properties

Several correctness properties were validated, reflecting the key requirements of the proposed system as shown in Table 2.

1) Safety Properties. Safety checks confirm the system never performs unsafe or contradictory actions:

— If CO_2 leakage is detected (`sensor.co2yes==true`), then the system must switch off the CO_2 source (`co2.switch_off==true`).

— If sufficient product weight is detected (`sensor.weight > 1000`), then no new order is allowed (`order.p < 1`).

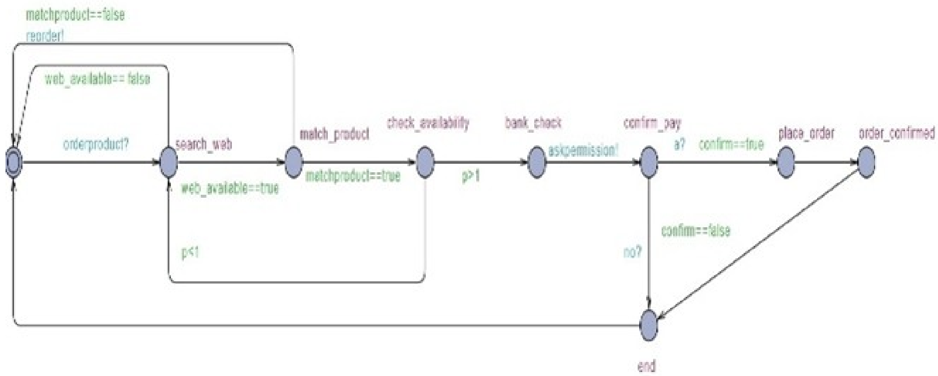

Fig. 4. Order process module with weight sensor and IR sensor

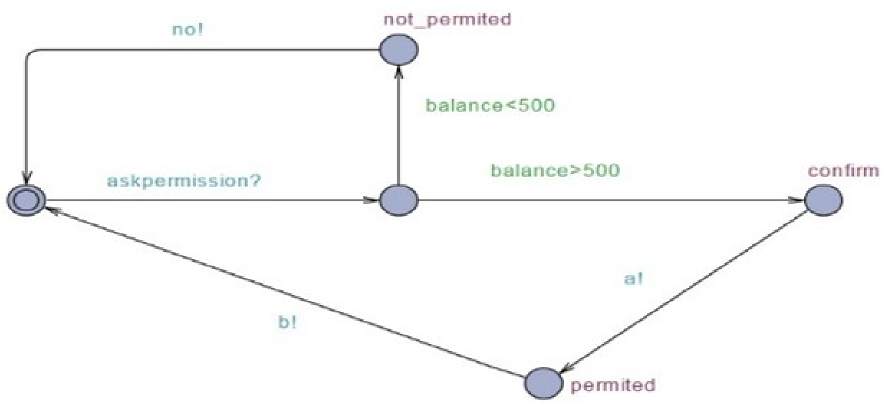

Fig. 5. Authorization of bank process module

— If weight falls below threshold for more than five days (`sensor.day>5`), then an order must be placed (`order.p > 1`).

2) Liveness Properties. An initiated order request always progresses to balance verification (`bank.balance>500`) before completion.

3) Deadlock Freedom. Concurrent processes (sensor monitoring, order placement, bank authorization) must not block each other. The property `A[] not deadlock` was tested.

4) Reachability Properties. Critical states must remain accessible under valid conditions:

— `E<>((sensor.weight>1000) imply (sensor.ordercancel==true))` ensures cancellation is reachable when stock is sufficient.

— `Ex((sensor.co2yes==false) imply (co2.switch_off==false))` ensures normal operation continues when no leakage occurs.

5.3 Verification Results

Representative verification outputs demonstrate correctness across all criteria:

— `E<>((sensor.weight>1000) imply (order.p>1))` $\rightarrow$ Satisfied; validates that order placement follows weight conditions.

Table 2. Summary of formal verification outcomes using UPPAAL

Property Tested	Formula	Outcome	Verification Time / Peak Memory
Safety (CO_2 leakage handled)	`sensor.co2yes -> co2.switch off`	Satisfied	0s / 46,952KB
Safety (avoid redundant orders)	`sensor.weight > 1000 -> order.p < 1`	Satisfied	0s / 46,944KB
Timely replenishment	`sensor.day > 5 -> order.p > 1`	Satisfied	0s / 46,956KB
Liveness (order progresses)	`order.p > 1 -> bank.balance > 500`	Satisfied	0s / 46,952KB
Deadlock freedom	`A[] not deadlock`	Satisfied	0.063s / 49,936KB
Reachability (cancellation)	`sensor.weight > 1000 -> ordercancel`	Satisfied	0.015s / 45,440KB
Normal operation	`¬sensor.co2yes -> ¬co2.switch off`	Satisfied	0s / 46,944KB

— `E<>((order.p>1) imply (bank.balance>500))` $\to$ Satisfied; confirms financial pre-check is always performed.

— `E<>((sensor.co2yes==true) imply (co2.switch_off==true))` $\to$ Satisfied; ensures CO_2 hazard is handled automatically.

— `A[] not deadlock` $\to$ Satisfied in 0.063s; system remains deadlock free.

5.4 Interpretation of Results

The verification confirms that the proposed system satisfies essential correctness criteria:

— **Safety:** No unsafe action or unnecessary order or unhandled CO_2 leakage is permitted.

— **Liveness:** All initiated processes eventually progress, avoiding starvation.

— **Deadlock Freedom:** Parallel modules never freeze the system.

— **Reachability:** Key outcomes such as order placement, cancellation, safety actions are always attainable.

The verification results demonstrate that the multi-agent probabilistic reasoning formalism, when instantiated in a smart fridge environment, operates correctly under diverse contextual conditions. By combining sensor-driven triggers with probabilistic reasoning and formally validated properties, the framework guarantees safe, reliable, and adaptive decision-making. This ensures that the architecture is not only theoretically robust but also practically verifiable for real-world deployments.

6 Conclusion

This paper presented a novel ontology-driven, probabilistic reasoning-based multi-agent formalism for smart environments, with a focus on managing inconsistency and uncertainty in safety-critical decision-making. Unlike traditional approaches that rely solely on deterministic ontology reasoning or isolated probabilistic models, our framework unifies OWL 2 RL ontologies, SWRL rules, multi-entity Bayesian networks and distributed agent reasoning into a layered architecture capable of adaptive and proactive decision support.

The proposed formalism was instantiated and evaluated through a smart fridge case study. Ontologies were developed to capture contextual knowledge, agents were designed to represent environmental entities and update beliefs dynamically, and probabilistic reasoning was employed to handle incomplete and noisy data. Formal verification using the UPPAAL model checker demonstrated that the system satisfies key correctness criteria, including safety, liveness, deadlock freedom, and reachability.

The verification results confirmed that the system reliably prevents redundant unsafe actions or unhandled CO_2 leakage, guarantees the progression of the process, and maintains stability under concurrent operations. A scalability analysis further indicated that the architecture can handle increasing numbers of sensors and agents with minimal performance degradation.

Beyond technical validation, the proposed approach offers broader practical implications. By combining semantic interoperability with probabilistic inference, the system provides both explainability and robustness, ensuring user trust in dynamic environments. Although demonstrated on a smart fridge, the formalism is domain-agnostic and can be readily adapted to healthcare monitoring, intelligent transportation, or energy management systems where uncertainty and safety are critical.

Future work will focus on extending the framework with predictive probabilistic reasoning for forecasting user behavior and resource needs, integrating reinforcement learning for adaptive agent collaboration, and deploying large-scale prototypes in real-world IoT ecosystems. These directions aim to evolve the system into a state-of-the-art decision-making platform capable of supporting highly reliable, scalable, and context-aware smart environments.

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