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An Agent-Based Methodology for Dealing with Chemical Weapons Agents in Manmade Disasters and Their Impact on Agriculture

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Abstract

Over the last years, natural hazards are increasing leading to a variety of difficult to solve issues. Yet, manmade disaster pose even equal or sometimes even more serious threats. Hence, it is important to study such threats, identify and propose measurements in order to deal with them. Actually, dealing with the consequences of chemical weapons agents in manmade disasters is a complex and challenging task that requires a systematic approach and coordination among various parties. To this end, agent-based modeling (ABM) is a useful methodology that can be employed to study and simulate the behavior of chemical agents, responders, and affected populations in such cases. ABM is a computational modeling technique that represents individual agents with specific attributes, behaviors, and interactions within a simulated environment. This paper aims to identify risks associated with manmade disasters while it proposes the development of an integrated framework to mitigate such disasters, with a primary focus on enhancing the capabilities of Civil Protection Personnel and the private sector Safety and Security Personnel. More specifically, the paper focuses on the use of chemical weapons agents, which are chemicals deliberately employed to cause harm through their toxic properties.

*Keywords:*Artificial Intelligence, Intelligent Agents, Chemical Weapons Agents

1. Introduction

Natural hazards are increasing over the last decades worldwide. Despite the fact that they cause serious disasters, we should not omit the threats posed by manmade disasters.

Manmade disasters have a diverse range of risks, varying in severity and consequences, leading to a need for comprehensive policies and trained responders. The outbreak of the COVID-19 pandemic highlighted societies' vulnerability to risks and dangers, emphasizing the importance of resilient Civil Protection and Safety and Security Personnel in an ever-evolving world.

This paper aims to identify potential risks associated with manmade disasters and the challenges they present. It envisions the development of an integrated framework to mitigate such disasters, with a main focus on enhancing the capabilities of Civil Protection Personnel and the private sector Safety and Security Personnel. Specifically, the paper focuses on the use of chemical weapons agents, which are chemicals that can cause harm through their toxic properties.

Investing in an autonomous and intelligent approach to disaster management, the Internet of Things (IoT) seems as a transformative extension of IT technology [2]. The IoT connects devices, services, and even humans, allowing them to communicate and make informed decisions. While current IoT practices often involve sending data to the Cloud for processing, the future IoT will employ Intelligent Agents (IAs) that can add autonomy, context awareness, and intelligence at the device level. With a projected twenty-nine billion connected devices by the year's end, this shift promises to unlock new value and opportunities across various industries, including civil protection.

The proposed decentralized approach advocates combining devices with intelligent agents to form an Internet of Smart Things. Intelligent Agents serve as a promising technology, offering an alternative to traditional human-object interactions. Their autonomous representation of people, devices, or services enables them to find applications in various domains, including crisis management and green growth.

This study introduces a rule-based methodology that empowers agents to conduct monitoring, issue warnings, and make decisions without requiring human intervention. Combining agent technology with the microservice architecture, the methodology fosters modular design and facilitates proper information exchange among agents and things. This approach ensures secure and robust transactions, maximizes interoperability, reusability, and automation, ultimately enhancing overall efficiency.

The subsequent sections of this paper delve into the details of the proposed rule-based methodology, exploring its potential to revolutionize disaster management by leveraging the power of autonomous and intelligent IoT-enabled Intelligent Agents. This methodology aims to pave the way for a safer and more resilient future in the face of manmade disasters by providing self-governing and adaptable systems.

The rest of the paper is organized as follows: In Section 2 we review the main categories of the chemical weapons agents. In Section 3 we discuss intelligent agents and defeasible logic. The methodology of our approach, including the smart control and decision-making is discussed in Section 4. Ultimately, we summarize our conclusions on Section 5.

2. Chemical Weapons Agents

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Chemical weapons agents can be categorized based on their chemical composition and the effects they produce. These categories are recognized under the Chemical Weapons Convention (CWC), an international treaty that prohibits the development, production, stockpiling, and use of chemical weapons. The categories are as follows:

2.1 Nerve Agents
These are highly toxic chemicals that disrupt the normal functioning of the nervous system. They inhibit the activity of acetylcholinesterase, an enzyme that regulates the neurotransmitter acetylcholine. As a result, nerve agents cause a range of symptoms, including respiratory distress, convulsions, paralysis, and ultimately, death. Examples include Sarin (GB), Soman (GD), Tabun (GA), and VX.

2.2 Blister Agents (Vesicants)
Blister Agents (Vesicants): These chemicals cause severe skin, eye, and respiratory tract irritation upon contact. They can cause large, painful blisters on the skin and severe chemical burns. Examples include Sulfur Mustard (HD), Nitrogen Mustard (HN), and Lewisite (L).

2.3 Blood Agents
Blood agents are toxic chemicals that disrupt the body's ability to utilize oxygen. They typically act by interfering with enzymes involved in cellular respiration, leading to suffocation. Examples include Hydrogen Cyanide (AC) and Cyanogen Chloride (CK).

2.4 Choking Agents (Pulmonary Agents)
Choking agents are volatile chemicals that cause damage to the respiratory system. They irritate the lungs and can lead to pulmonary edema, which results in severe breathing difficulties and death. Examples include Chlorine ($Cl2$) and Phosgene (CG).

2.5 Incapacitating Agents
These agents are designed to temporarily disable individuals without causing significant harm or lethality. They can induce various physiological and psychological effects, such as sedation, confusion, hallucinations, or paralysis. BZ (3-quinuclidinyl benzilate) is an example of an incapacitating agent.

2.6 Riot Control Agents (Tear Gas)
While not typically considered lethal chemical weapons, riot control agents are still categorized under the CWC. They are used for law enforcement purposes and cause irritation of the eyes, nose, and throat, leading to tears, coughing, and temporary incapacitation. Common examples include CS (Orthochlorobenzylidene malononitrile) and CN (Chloroacetophenone).

It is essential to note that the use of chemical weapons is strictly prohibited under international law due to their indiscriminate and inhumane nature. The Chemical Weapons Convention aims to eliminate the production and use of these weapons and promote their peaceful and safe destruction.

3. Intelligent Agents and Defeasible Logic

Intelligent Agents and Defeasible Logic can be combined in order to provide a powerful decision-making and reasoning system that enables agents to make autonomous and context-aware decisions based on incomplete and sometimes conflicting information. Below is discussed how intelligent agents and defeasible logic can be combined and used:

3.1 Intelligent Agents
Intelligent agents are entities that can operate autonomously, sense their environment, and take actions to achieve their goals. They have the ability to reason, learn from past experiences, and communicate with other agents and entities. These agents can be designed to represent human or virtual entities, services, or devices in a multi-agent system. [1]

3.2 Defeasible Logic
Defeasible logic is a nonmonotonic reasoning formalism that deals with incomplete and conflicting information. It supports the representation of rules that can be defeated and derives plausible conclusions from the available information. In defeasible logic, a knowledge base consists of facts, strict rules, defeasible rules, and defeaters. The superiority relationship among rules allows for resolving conflicts and determining which rules override others. [4]

3.3 Combining Intelligent Agents and Defeasible Logic
We can enhance their reasoning capabilities in dynamic and uncertain environments by incorporating defeasible logic into the decision-making process of intelligent agents. The combination can be achieved by:

3.3.1 Representing Knowledge as a Defeasible Theory
The knowledge base of each intelligent agent can be represented as a defeasible theory (D) consisting of facts (F), strict rules (R), and defeasible rules (R) relevant to its domain. Each agent can maintain its own defeasible theory, representing its beliefs, goals, and reasoning rules.

3.3.2 Handling Incomplete and Conflicting Information
Intelligent agents often operate in environments where information is incomplete or contradictory. Defeasible logic allows agents to reason with such information and derive plausible conclusions. Conflicting rules can be managed using the superiority relationship to prioritize certain rules over others.

3.3.3 Real-time Assessment and Decision-making
Intelligent agents equipped with defeasible logic can perform real-time assessment of their environment and make informed decisions based on the available information. They can react to changes in their surroundings, perceive hazards or risks, and take proactive measures to achieve their goals or respond to external stimuli.

3.3.4 Communication and Collaboration
Intelligent agents' communication abilities are vital for coordination and collaboration. Defeasible logic enables agents to exchange information, share knowledge, and negotiate based on their respective defeasible theories. They can resolve conflicts, reach agreements, and collectively make decisions to achieve common objectives.

3.3.5 Learning and Adaptation
Intelligent agents can learn from their past experiences using machine learning techniques. Defeasible logic can be integrated into the learning process, allowing agents to refine their defeasible theories based on new information and update their reasoning rules to adapt to changing environments.

3.3.6 Multi-Agent Systems as Virtual Social Communities

The combination of intelligent agents and defeasible logic can create dynamic multi-agent systems that function as virtual social communities. Each agent plays a unique role, communicating and interacting with others to achieve individual and collective goals. The defeasible reasoning capabilities enable agents to collaborate effectively, reason about their actions and the actions of others, and collectively make decisions.

In summary, by combining intelligent agents and defeasible logic, we can create a sophisticated decision-making and reasoning framework that empowers agents to operate autonomously, reason with incomplete and conflicting information, communicate, learn, and adapt in dynamic environments. This approach is particularly useful in domains where uncertainty and ambiguity are prevalent, allowing agents to make context-aware decisions in real-time.

4. Smart Control and Decision-Making

As already discussed, a decision-making mechanism for chemical weapons agents can be designed using defeasible logic. In this context, we can define the characteristics and preferences of each chemical agent, along with a set of rules to categorize and assess their potential risks [7][8][9][10]. The approach for the different categories of chemical weapons agents is presented below:

4.1 Characteristics and Preferences

Our approach models three main types of system entities; namely agents that represent human or virtual entities, services and devices. All types of entities are represented as agents while microservice architecture was used for the implementation of services and devices, achieving the necessary functionalities and reducing the common issue of device handling [4][5][6]. For each chemical weapons agent, we define a set of characteristics (C) and preferences (P) that represent their chemical composition, effects, and potential risks, (C_x^k& P_x^m | k,m ∈ [1, N], x ≡ entity).These characteristics and preferences are assigned weight values to indicate their importance at the range [0, 1]; namely W_c^k & W_p^m | k,m ∈ [1, N], c ≡ characteristic, p ≡ preference.

4.2 Defeasible Rules

We use defeasible rules to categorize and assess the risks associated with each chemical agent. Each rule consists of antecedents (conditions) and consequents (conclusions). The rules can be of the strict or defeasible type [11][12]. Examples of Defeasible Rule for Nerve Agents (A) and Blister Agents (B) are presented below:

Rule A1: nerve_agent(X) -> toxic(X), disrupts_nervous_system(X).
Rule B1: blister_agent(X) -> skin_irritation(X), eye_irritation(X), respiratory_irritation(X).

4.3 Superiority Relationship

As different chemical agents may have conflicting rules, we establish a superiority relationship (>), which will help determine which rule prevails in case of conflicts. An example of Superiority Relationship is Rule A1 > Rule B1, which indicates that the conclusion of Rule A1 is superior to Rule B1 in case of conflicts between nerve agents and blister agents.

4.4 Assess Chemical Agent Cases

For each chemical agent case, we evaluate its characteristics and preferences based on the defined rules. We can determine the risk level and potential effects of each agent, by considering the weight values and superiority relationship [13][14]. An example of Defeasible Rule for Assessing Risk Level is the following:

Rule R1: case(X) -> high_risk(X) :- nerve_agent(X), toxic(X), disrupts_nervous_system(X), weight(toxic(X), ?w1), weight(disrupts_nervous_system(X), ?w2), ?w1 + ?w2 >= risk_threshold_high.

An example of Defeasible Rule for Assessing Potential Effects is the following:

Rule R2: case(X) -> severe_effects(X) :- blister_agent(X), skin_irritation(X), eye_irritation(X), respiratory_irritation(X), weight(skin_irritation(X), ?w1), weight(eye_irritation(X), ?w2), weight(respiratory_irritation(X), ?w3), ?w1 + ?w2 + ?w3 >= effect_threshold_severe.

4.5 Handle Conflicts and Priorities

If there are conflicts between different rules in assessing a chemical agent case, we use the established superiority relationship to resolve them. The rule with higher priority prevails in determining the risk level or potential effects of the agent. An example of Defeater Rule for Prioritization is the following:

Rule R3: case(X) -> low_risk(X) :- nerve_agent(X), toxic(X), disrupts_nervous_system(X), Rule A1 > Rule R1.

Hence, we can effectively categorize chemical weapons agents and assess their potential risks and effects by employing this defeasible logic-based decision-making mechanism. The system will provide informative messages, warnings, or suggestions to users based on the evaluations of each agent case. The approach can be extended and refined to include more complex rules and considerations for a comprehensive decision-making process.

5. Example Use Case: Chemical Weapons Detection and Response

In a major metropolitan city, a terrorist threat involving the use of chemical weapons agents is reported. The city's Civil Protection and Safety and Security Personnel need to quickly assess the situation, detect the presence of chemical agents, and respond effectively to ensure the safety and well-being of the population. Using the proposed integrated framework of intelligent agents and defeasible logic, the city's disaster management system is equipped with a network of IoT-enabled sensors and devices placed strategically throughout the city. These sensors can detect various chemical agents and transmit real-time data to the intelligent agents. Below is given briefly how the system operates in this scenario:

Sensor Data Collection: IoT-enabled sensors detect the presence of chemical agents in the environment and gather relevant data, such as the type of agent, concentration levels, and geographical locations.

Agent Representation: Intelligent agents within the system represent various entities, including the sensors, local emergency response teams, and relevant government agencies. Each agent maintains its defeasible theory, incorporating characteristics and preferences associated with specific chemical agents.

Defeasible Rules Application: Defeasible logic is employed to categorize and assess the risks posed by the detected chemical agents. For instance, when the sensors identify nerve agents, defeasible rules apply that establish a superiority relationship between nerve agents and other categories, prioritizing their assessment.

Risk Assessment: The intelligent agents process the sensor data and apply the defeasible rules to evaluate the risks associated with each detected chemical agent. The system calculates the risk level and potential effects of each agent, taking into account factors such as toxicity, disruption to the nervous system, and potential harm to human health.

Decision-making and Response: Based on the risk assessment results, the intelligent agents make context-aware decisions regarding the appropriate response. For instance, if a nerve agent with a high-risk level is detected in a densely populated area, the system triggers an emergency alert, notifies the local emergency response teams, and initiates evacuation procedures for affected areas.

Communication and Collaboration: The intelligent agents facilitate communication and collaboration among different entities. They exchange information with the relevant agencies, share the risk assessment results, and collectively decide on appropriate measures for containment and neutralization.

Real-time Adaptation: The system continuously monitors the environment for changes, allowing intelligent agents to adapt their responses based on updated information. For instance, if the concentration levels of a detected chemical agent increase rapidly, the system can redirect response teams to prioritize affected areas.

Learning and Improvement: As the system operates and responds to different scenarios over time, the intelligent agents learn from past experiences using machine learning techniques. They refine their defeasible theories and reasoning rules to enhance decision-making capabilities in future incidents.

The disaster management system in the city can effectively detect and respond to potential chemical weapons threats by combining intelligent agents and defeasible logic. The autonomous and context-aware decision-making capabilities of the intelligent agents, along with real-time data processing and collaboration, enable the city's Civil Protection and Safety and Security Personnel to act swiftly and efficiently, mitigating the risks and protecting the population from harm.

Below are some rule examples for the proposed intelligent agent-based system for chemical weapons detection and response:

5.1 Defeasible Rules for Categorization

Rule A1: nerve_agent(X) -> toxic(X), disrupts_nervous_system(X).
Rule A2: blister_agent(X) -> skin_irritation(X), eye_irritation(X), respiratory_irritation(X).
Rule A3: blood_agent(X) -> disrupts_oxygen_utilization(X).
Rule A4: choking_agent(X) -> respiratory_damage(X).
Rule A5: incapacitating_agent(X) -> physiological_effects(X).
Rule A6: riot_control_agent(X) -> irritates_senses(X).

5.2 Superiority Relationship for Conflict Resolution

Rule A1 > Rule A2
Rule A1 > Rule A3
Rule A1 > Rule A4
Rule A1 > Rule A5
Rule A1 > Rule A6
Rule A2 > Rule A3
Rule A2 > Rule A4
Rule A2 > Rule A5
Rule A2 > Rule A6
Rule A3 > Rule A4
Rule A3 > Rule A5
Rule A3 > Rule A6
Rule A4 > Rule A5
Rule A4 > Rule A6
Rule A5 > Rule A6

5.3 Defeasible Rules for Risk Assessment

Rule R1: case(X) -> high_risk(X) :- nerve_agent(X), toxic(X), disrupts_nervous_system(X), weight(toxic(X), ?w1), weight(disrupts_nervous_system(X), ?w2), ?w1 + ?w2 >= risk_threshold_high.
Rule R2: case(X) -> moderate_risk(X) :- blister_agent(X), skin_irritation(X), eye_irritation(X), respiratory_irritation(X), weight(skin_irritation(X), ?w1), weight(eye_irritation(X), ?w2), weight(respiratory_irritation(X), ?w3), ?w1 + ?w2 + ?w3 >= risk_threshold_moderate.
Rule R3: case(X) -> low_risk(X) :- blood_agent(X), disrupts_oxygen_utilization(X), weight(disrupts_oxygen_utilization(X), ?w1), ?w1 >= risk_threshold_low.
Rule R4: case(X) -> low_risk(X) :- choking_agent(X), respiratory_damage(X), weight(respiratory_damage(X), ?w1), ?w1 >= risk_threshold_low.
Rule R5: case(X) -> low_risk(X) :- incapacitating_agent(X), physiological_effects(X), weight(physiological_effects(X), ?w1), ?w1 >= risk_threshold_low.
Rule R6: case(X) -> low_risk(X) :- riot_control_agent(X), irritates_senses(X), weight(irritates_senses(X), ?w1), ?w1 >= risk_threshold_low.

5.4 Defeater Rule for Prioritization

Rule R7: case(X) -> low_risk(X) :- nerve_agent(X), toxic(X), disrupts_nervous_system(X), Rule A1 > Rule R1.

5.5 Defeasible Rule for Response

Rule RESP1: case(X) -> initiate_evacuation(X) :- high_risk(X).
Rule RESP2: case(X) -> deploy_hazmat_team(X) :- high_risk(X).
Rule RESP3: case(X) -> notify_health_authorities(X) :- high_risk(X).
Rule RESP4: case(X) -> monitor_concentration_levels(X) :- moderate_risk(X).

In this example, the system evaluates the detected chemical agent cases (X) using the defeasible rules for categorization and risk assessment. The system resolves conflicts between different rules using the established superiority relationship. Depending on the risk level, the system triggers specific responses, such as initiating evacuation, deploying hazmat teams, notifying health authorities, or monitoring concentration levels. Please note that the actual rule definitions, weight values, and risk thresholds would be determined based on domain-specific knowledge and expert input to ensure the system's accuracy and effectiveness in real-world scenarios.

6. Impact on Agriculture

So far, it is clear that chemical weapons agents could seriously affect communities. Yet, chemical weapons agents can also pose significant threats to agricultural systems. Crop damage can manifest as leaf scorch, wilting, and discoloration, ultimately leading to significant yield losses, economic losses for farmers or even complete crop failure while soil contamination could turn land unusable for years. Livestock contamination through contaminated pastures or water sources can result in health issues, reduced productivity, and increased mortality rates. Furthermore, soil contamination can degrade soil fertility and microbial activity, impacting long-term agricultural productivity. As a result, agricultural disruption can affect food security and human health, leading among others to shortages and price increases. Hence, in order to address these challenges, we incorporate into our methodology agricultural-specific agents, namely agents that represent farms, livestock, and crops. The aim of these agents is to identify agricultural vulnerabilities to different chemical agents. Of course, we need sensors established in agricultural areas, such as fields, in order to receive real-time information on environmental conditions and potential contamination levels. To this end, the proposed framework considers considering factors such as crop type, livestock species, and local environmental conditions. Additionally, the intelligent agents can incorporate knowledge, by adding the appropriated rules in their knowledge base, agricultural mitigation strategies, such as decontamination procedures, crop protection measures, and livestock safety protocols. More specifically, intelligent agents will be able to monitor environmental conditions, assess the vulnerability of specific crops and livestock to detected agents, and predict potential impacts on agricultural production. Moreover, they could also communicate with other agents, such as those representing emergency responders or government agencies, to coordinate responses and minimize agricultural losses.

A use case depicting the added value of the methodology in the agriculture sector is presented below. In this simulation scenario, a farmer observes unusual symptoms in his wheat crop, namely wilting, discoloration, and stunted growth. The farmer suspects a potential chemical exposure. Meanwhile, supposing that there is a real-time monitoring based on sensors, the agent-based system detects the issue. More specifically, the agricultural monitoring agent receives sensor data from the farm, including soil moisture levels, temperature, and recent weather patterns. The agent firstly analyzes the observed crop symptoms, namely wilting, discoloration, stunted growth, and compares them to known effects of various chemical agents. Part of the rules related to crop symptoms are:

Rule A1: crop_wilting(X) -> potential_chemical_exposure(X) [weight: 0.7]
Rule A2: crop_discoloration(X) -> potential_chemical_exposure(X) [weight: 0.8]
Rule A3: crop_stunted_growth(X) -> potential_chemical_exposure(X) [weight: 0.6]
Rule A4: multiple_symptoms(X) -> increase_suspicion(X) [weight: 0.9]

Next, the agent considers environmental factors such as recent weather patterns, proximity to potential contamination sources (e.g., industrial sites), and historical data on past chemical incidents in the region. Part of the rules related to environmental factors are:

Rule B1: drought_conditions(X) -> increase_stress_on_crops(X) [weight: 0.6]
Rule B2: proximity_to_industrial_site(X) -> potential_contamination_source(X) [weight: 0.8]
Rule B3: recent_chemical_incidents(X) -> increase_alert_level(X) [weight: 0.7]

Following, the crop symptoms and the environmental factors, the agent system can proceed to risk assessment. For instance, if the risk level is high indicating potential chemical exposure (Rule R1), the agent alerts local authorities such as the agriculture department or emergency services (Rule A1) or make some proposals (Rule A2/Rule A3).

Rule R1: case(X) -> high_risk(X) :- potential_chemical_exposure(X), increase_suspicion(X), increase_stress_on_crops(X), weight(potential_chemical_exposure(X), ?w1), weight(increase_suspicion(X), ?w2), weight(increase_stress_on_crops(X), ?w3), ?w1 + ?w2 + ?w3 >= 2.0
Rule R2: case(X) -> moderate_risk(X) :- potential_chemical_exposure(X), increase_stress_on_crops(X), weight(potential_chemical_exposure(X), ?w1), weight(increase_stress_on_crops(X), ?w2), ?w1 + ?w2 >= 1.2
Rule R3: case(X) -> low_risk(X) :- potential_chemical_exposure(X), normal_conditions(X)
Rule A1: high_risk(X) -> alert_authorities(X)
Rule A2: high_risk(X) -> recommend_soil_testing(X)
Rule A3: high_risk(X) -> recommend_crop_sampling(X)
Rule A4: moderate_risk(X) -> increase_monitoring(X)
Rule A5: low_risk(X) -> continue_monitoring(X)

Of course, there are superiority relationships for these rules:

Rule A1 > Rule A4
Rule A2 > Rule A4
Rule A3 > Rule A4
Rule R1 > Rule R2
Rule R1 > Rule R3

At this point, it is worth mentioning that the assigned to each rule weights reflect the relative importance or confidence in that particular rule. Hence, higher weights indicate greater confidence in the conclusion of the rule. For instance, in Rule R1, the combined weight of the contributing factors, namely potential_chemical_exposure, increase_suspicion, increase_stress_on_crops must exceed a threshold value, here 2.0, to classify the risk as high.

Furthermore, the system can dynamically adjusts rule priorities based on several factors. More specifically, the rule prioritization is affected by the observed symptoms and their severity such as the extent of crop wilting or the number of livestock affected. In this context, more severe symptoms will trigger higher priority for those rules that are associated with more dangerous chemical agents. Another example, is the environmental conditions, such as extreme weather events that could increase vulnerability and consequently rule priority for the rules that deal with environmental stress factors. Another factor that could lead to dynamic priority increase is the existence of previous threats, based on historical data on chemical incidents in the region. Of course, rule priorities are dynamically updated not only based on historical data but also on real-time sensor data, such as changes air quality. As a result, the system could be adaptive, proving more accurate risk assessments. The system can further refine rule prioritization by incorporating machine learning techniques. Hence, this dynamic adjustment of rule priorities enhances the ability of the system to adapt to changing conditions, improve the accuracy of risk assessments, and provide more effective and timely responses to chemical threats.

7. Scalability Considerations

A critical aspect of our agent-based methodology is undoubtedly its scalability, especially for real-world cases where there are many interacting agents, a high volume of data and heterogeneous study areas. In this context, one of the issues is the computational overhead. It is obvious that the computational needs will be increased as the number of agents, sensors, and data streams will increase. The answer to this challenge is the distributed processing. More specifically, we desing intelligent agent cluster, namely we allow agents that deal with similar crops or farming areas to interacting forming a group. This approach will allow not only efficient processing by using task sharing protocols, i.e. contract net, but also it will form a local decision-making mechanism reducing i.e. the load to central servers or other busy agents. Another approach in the same direction, that will be studied in the future it that of using edge computing, where edge computing devices such as microcontrollers or small servers will perform initial data processing reducing the amount of data transmitted to the central system or other agents and minimizing network traffic. Hence, we aim not only to a distributed approach but also to an edge-based one.

Another issue is possible communication bottlenecks. In order to avoid such cases, we plan to implement data aggregation techniques to reduce the volume of data transmitted between agents. For example, instead of transmitting raw sensor readings from each individual sensor, responsible controllers/agents will aggregate data from multiple sensors within a cluster and transmit only the aggregated values. Additionally, a hierarchical communication strategy could be adopted. This strategy indicated that agents are categorized on three levels, namely lower-, intermediate- and higher-level agents. Lower-level agents transmit data to intermediate agents, which then summarize and forward the information to higher-level agents, so, the amount of data transmitted across the network is reduced. Moreover, when the amount of data exceeds the local server capacity, we plan to transfer the system to a cloud-based storage. There are already plenty of services available, such as Amazon S3, Google Cloud Storage, that could store and manage large volumes of sensor data, historical records, and model parameters. Of course, the strategy of each agent will remain private and if needed encrypted.

Finally, we plan to conduct extensive simulations to evaluate system performance under different load conditions, varying the number of agents, data volumes, and network traffic. This will allow us to monitor system performance and identify bottlenecks. System parameters, such as communication protocols, data aggregation strategies, and resource allocation could then be adjusted based on the aforementioned solutions.

8. Conclusions and Recommendations

In conclusion, the integration of intelligent agents and defeasible logic provides a robust and effective framework for decision-making and reasoning, not only in environmental hazards but also in the complex and critical domain of chemical weapons agents. Intelligent agents equipped with autonomy, reactivity, and communication abilities can represent diverse entities, services, and devices related to chemical agents. These agents have the capability to perceive their environment, gather data from sensors, and learn from historical information to form knowledge bases as defeasible theories. This knowledge includes characteristics and preferences of various chemical agents, along with the risks and potential effects associated with each category. Defeasible logic proves invaluable in handling the inherent uncertainties and incomplete information present in the analysis of chemical weapons agents. Hence, the system can categorize nerve agents, blister agents, blood agents, choking agents, incapacitating agents, and riot control agents based on their chemical composition and effects by employing defeasible rules. The superiority relationship among rules allows agents to prioritize and resolve conflicts in their assessments.

This integrated approach enables intelligent agents to assess and evaluate the risks and potential effects of different chemical agents in real-time. Agents can reason and make context-aware decisions by taking into account the weighted characteristics and preferences, determining the risk levels of each agent and suggesting appropriate responses or actions. Moreover, the ability to communicate and collaborate with other agents enhances the system's overall effectiveness. Agents can share information, negotiate priorities, and collectively analyze situations involving multiple chemical agents. This collaborative decision-making mimics the complex interactions present in real-world scenarios, facilitating effective response strategies and ensuring a comprehensive assessment of the chemical threats.

The significance of this approach extends beyond environmental monitoring and risk management to address critical security and defense challenges. We empower decision-makers to respond swiftly and efficiently to chemical weapons agents' threats by leveraging intelligent agents and defeasible logic. The framework assists in making well-informed decisions that protect human lives, minimize environmental impacts, and prevent catastrophic events. As technology progresses, the integration of intelligent agents and defeasible logic holds great promise in advancing the field of artificial intelligence and multi-agent systems. With ongoing developments and refinements, this combined approach will continue to play a pivotal role in addressing complex, uncertain, and high-stakes situations, safeguarding societies from the risks posed by chemical weapons agents.

References

[1] K. Kravari and N. Bassiliades, "StoRM: A social agent-based trust model for the internet of things adopting microservice architecture," *Simulat. Modell. Pract. The.*, vol. 94, pp. 286–302, Jul. 2019, doi: https://doi.org/10.1016/j.simpat.2019.03.008.

[2] A. Whitmore, A. Agarwal, and L. Da Xu, "The Internet of Things—A survey of topics and trends," *Inform. Sys. Frontiers*, vol. 17, no. 2, pp. 261–274, Mar. 2014, doi: https://doi.org/10.1007/s10796-014-9489-2.

[3] D. Nute, "Defeasible Logic," in *Web Knowl. Manag. Decis. Supp.*, vol. 2543, O. Bartenstein, U. Geske, M. Hannebauer, and O. Yoshie, Eds., in Lecture Notes in Computer Science, vol. 2543. , Berlin, Heidelberg: Springer Berlin Heidelberg, 2003, pp. 151–169. doi: 10.1007/3-540-36524-9_13.

[4] I. Lee and K. Lee, "The Internet of Things (IoT): Applications, investments, and challenges for enterprises," *Busin. Horiz.*, vol. 58, no. 4, pp. 431–440, Jul. 2015, doi: https://doi.org/10.1016/j.bushor.2015.03.008.

[5] M. Garriga, "Towards a Taxonomy of Microservices Architectures," in *Softw. Eng. Formal Meth.*, vol. 10729, A. Cerone and M. Roveri, Eds., in Lecture Notes in Computer Science, vol. 10729, Cham: Springer International Publishing, 2018, pp. 203–218. doi: 10.1007/978-3-319-74781-1_15.

[6] R. Gore, C. Lemos, F. L. Shults, and W. J. Wildman, "Forecasting Changes in Religiosity and Existential Security with an Agent-Based Model," *J. Arti.l Societ. Soc. Simul.*, vol. 21, no. 1, pp. 1-4, Jan. 2018, doi: https://doi.org/10.18564/jasss.3596.

[7] "Transforming our world: the 2030 Agenda for Sustainable Development." United Nations, Oct. 21, 2015. [Online]. Available: https://docs.un.org/en/A/RES/70/1

[8] G Tyler Miller, *Sustaining the earth: an integrated approach*. Pacific Grove, Ca: Brooks/Cole, pp. 211-216, 2004, ISBN: 978-0-534-40088-0

[9] M. Alioto, Ed., *Enabling the Internet of Things*. Cham: Springer International Publishing, 2017. doi: 10.1007/978-3-319-51482-6.

[10] E. Amin, M. Abouelela, and A. Soliman, "The Role of Heterogeneity and the Dynamics of Voluntary Contributions to Public Goods: An Experimental and Agent-Based Simulation Analysis," *J. Artif. Societ. Soc. Simul.*, vol. 21, no. 1, Jan. 2018, doi: https://doi.org/10.18564/jasss.3585.

[11] M. J. MAHER, "Propositional defeasible logic has linear complexity," *The. Pract. Logic Program.*, vol. 1, no. 6, pp. 691–711, Nov. 2001, doi: https://doi.org/10.1017/s1471068401001168.

[12] N. Bassiliades, G. Antoniou, and I. Vlahavas, "A Defeasible Logic Reasoner for the Semantic Web," *Int. J. Seman. Web Inform. Sys.*, vol. 2, no. 1, pp. 1–41, Jan. 2006, doi: https://doi.org/10.4018/jswis.2006010101.

[13] E. Kontopoulos, N. Bassiliades, and G. Antoniou, "Visualizing Semantic Web proofs of defeasible logic in the DR-DEVICE system," *Knowledge-Based Sys.*, vol. 24, no. 3, pp. 406–419, Apr. 2011, doi: https://doi.org/10.1016/j.knosys.2010.12.001.

[14] Á. Carrera, C. A. Iglesias, J. García-Algarra, and Dušan Kolařík, "A real-life application of multi-agent systems for fault diagnosis in the provision of an Internet business service," *J. Netw. Comp. Applic.*, vol. 37, pp. 146–154, Jan. 2014, doi: https://doi.org/10.1016/j.jnca.2012.11.004