A Rule-Based Expert System for Post-War Building Assessment in Gaza (2025)

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Abstract—Post-war environments are often characterized by widespread destruction of urban infrastructure, necessitating efficient and reliable methods for assessing building safety and prioritizing reconstruction efforts. This study presents a rulebased expert system for post-war building assessment, specifically designed for the Gaza Strip, a region heavily affected by conflict and prolonged blockade. The system leverages fuzzy logic and inference mechanisms, including forward and backward chaining, to evaluate structural integrity and environmental risks, such as hazardous zones, radiation levels, and flood proximity. By integrating confidence-based rules, the system prioritizes actions based on severity and uncertainty, ensuring optimized resource allocation during recovery. Testing demonstrated the system's ability to process complex scenarios and deliver actionable insights. This research highlights the potential of intelligent systems to transform disaster recovery, offering a scalable and adaptable model for other conflictaffected regions.

Index Terms—Post-war building assessment, expert systems, rule-based systems, forward chaining, backward chaining, fuzzy logic, Gaza reconstruction, disaster recovery, resource prioritization.

I. INTRODUCTION

ost-war environments often leave behind extensive damage to urban infrastructure, posing significant risks to public safety and complicating recovery efforts. In Gaza, years of conflict and blockade have severely impacted the structural integrity of buildings, necessitating a reliable method to assess and prioritize reconstruction efforts [9], [15].

This study introduces a rule-based expert system for postwar building assessment in Gaza. By leveraging a combination of fuzzy logic, forward and backward chaining mechanisms, and confidence-based rules, the system aims to provide accurate, scalable, and timely assessments of structural damage. The system incorporates factors such as hazardous zones, radiation levels, and flood risks to prioritize actions and recommend mitigation strategies.

The expert system is designed not only to address immediate needs but also to support long-term recovery planning by ensuring that resources are allocated efficiently. This research contributes to the growing field of intelligent systems in disaster recovery, offering a scalable model that can be adapted for other post-conflict regions [1], [4].

II. STUDY AREA

The Gaza Strip, an area of approximately 365 square kilometers, is one of the most densely populated regions in the world. It is home to over 2.2 million people and has faced significant infrastructural and humanitarian challenges due to prolonged conflict, blockade, and recurrent hostilities. These challenges have led to widespread destruction of urban infrastructure, displacement of residents, and limited access to essential services such as water, electricity, and healthcare.

The damage caused by recent hostilities is illustrated in Fig. 1, which shows the extent of destruction across Gaza based on satellite data. This widespread destruction necessitates the development of systems that can efficiently prioritize reconstruction efforts and assess building safety under complex and uncertain conditions.

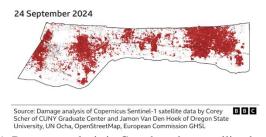


Fig. 1. Damage analysis in Gaza based on satellite data [15].

The humanitarian impact has been severe, with 90% of Gaza's population displaced at some point, as shown in Fig. 2. This displacement highlights the critical need for systems that can support decision-making processes in high-pressure scenarios, addressing both immediate and long-term reconstruction priorities.

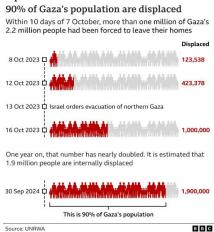


Fig. 2. Displacement statistics in Gaza [15].

Approximately 90% of Gaza's population is displaced, as illustrated in Fig. 2 [15]. Damage analysis conducted using satellite data highlights the widespread destruction across Gaza, as shown in Fig. 1 [15]. These factors make it an ideal case study for developing a rule-based expert system for postwar building assessment.

Geographically, the Gaza Strip is bordered by Israel to the north and east, Egypt to the south, and the Mediterranean Sea to the west. Fig. 3 illustrates the area's administrative divisions, refugee camps, and key crossings. These geographical constraints, combined with the area's high population density, create unique challenges for reconstruction and risk management. An expert system tailored to the Gaza Strip must account for these factors when generating recommendations.



Fig. 3. Map of Gaza Strip [16].

Geographically, the region shares borders with Egypt to the south and Israel to the east and north, with the Mediterranean Sea to the west. The Gaza Strip's administrative divisions and key locations are depicted in Fig. 3 [16].

The integration of an expert system into this context is essential for streamlining the decision-making process. By leveraging rule-based inference and fuzzy logic, the system can analyze factors such as structural damage, environmental risks, and proximity to hazardous zones to generate actionable recommendations. For example, the system prioritizes reconstruction efforts based on damage severity and proximity to critical infrastructure, ensuring optimal resource allocation in an environment with limited resources and high demand.

This study area provides a compelling use case for the expert system, as it addresses the unique challenges of post-conflict reconstruction in a highly complex environment. The integration of geographical, demographic, and infrastructural data into the expert system underscores its potential to support stakeholders in prioritizing efforts and ensuring the safety and resilience of Gaza's built environment.

III. SAMPLE KNOWLEDGE BASE RULES

The knowledge base is the core component of the expert system, containing a structured set of rules that guide the decision-making process. These rules integrate **fuzzy logic** to address uncertainties, **priority levels** to rank reconstruction needs, and **confidence metrics** to validate rule outcomes. By combining these components, the system provides actionable and informed recommendations tailored for post-war building assessments. Below are categorized examples of key rules from the knowledge base, each linked to relevant references where applicable:

A. Structural Integrity

• Rule: If cracks are severe and confidence in the damage assessment is high, then immediate reconstruction is prioritized [1], [13].

B. Hazardous Zones

• Rule: If the building is located in a hazardous zone with a confidence level above 0.6, reconstruction is delayed due to safety concerns [7].

C. Flood Proximity

• Rule: If the building is within 100 meters of a flood zone, moderate flood protection measures are recommended [10].

D. Radiation Levels

• Rule: If radiation levels exceed 20.0 μSv/h, prohibit rebuilding due to health risks [11].

E. Overcrowding

• Rule: If the population density exceeds safe thresholds, prioritize reconstruction to alleviate overcrowding [9].

IV. METHODOLOGY

The methodology for this research focuses on the design and implementation of a rule-based expert system for assessing post-war building conditions in Gaza. The system leverages fuzzy logic and inference mechanisms to handle complex scenarios with inherent uncertainties, enabling accurate prioritization of reconstruction efforts. Below, we outline the key components and processes of the system.

A. System Architecture

The expert system consists of three primary components:

- 1. **Inference Engine**: Processes the rules and facts using forward and backward chaining mechanisms to derive conclusions [17].
- 2. **Knowledge Base**: Contains a comprehensive set of rules addressing structural, environmental, and social factors that affect building safety [1], [3].
- 3. **User Interface**: Developed using Streamlit, the interface allows users to input building assessment data and view prioritized recommendations [17].

B. Fuzzy Logic and Confidence Handling

Fuzzy logic was employed to manage uncertainty in the assessment process. Membership functions were defined for

variables such as crack severity, flood zone proximity, and radiation levels. For example:

- Crack Severity: Classified as minor, moderate, or severe based on predefined thresholds [3], [6].
- Radiation Levels: Categorized as safe, moderate, or critical to guide reconstruction decisions [7], [11].

Confidence levels, ranging from 0.0 to 1.0, were used to scale the priority of actions based on the reliability of the input data [10]. Rules were designed to adjust decisions dynamically, ensuring flexibility and accuracy.

C. Inference Mechanisms

The system utilizes both forward and backward chaining to derive conclusions:

- Forward Chaining: Starts from known facts and applies rules to infer conclusions. For example, inputting crack severity and flood proximity triggers related actions automatically [17].
- Backward Chaining: Begins with a goal and works backward to verify the conditions required to achieve that goal. This mechanism is particularly useful for determining whether specific reconstruction actions are necessary [1].

D. Implementation Tools

The system was implemented in Python using the following tools:

- Experta: A rule-based framework for defining and processing expert system rules [17].
- Streamlit: For building an interactive user interface.

E. Testing and Validation

To validate the system, forward and backward chaining tests were conducted on three individual rules and three combined rules. Scenarios included varying crack severities, radiation levels, and proximity to hazardous zones. Results demonstrated the system's ability to process complex cases and prioritize actions effectively [1], [13], [14].

V. RESULTS

The results of the testing phase for the expert system demonstrated its effectiveness in processing complex scenarios and providing prioritized recommendations based on structural, environmental, and confidence-based rules. The testing was conducted on both individual and combined rules using forward and backward chaining mechanisms. Below are the key outcomes and their interpretations.

A. Forward Chaining Results

Forward chaining was tested using predefined facts to evaluate the system's ability to derive conclusions automatically.

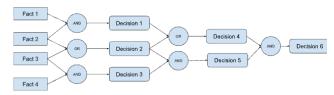


Fig. 4. Forward chaining flow chart [18].

Forward chaining process. Known facts trigger rules iteratively, leading to new conclusions until no further rules can be applied.

■ The following key results were observed:

1. Crack Severity Rule:

- Input: Crack width = 15.0 cm, confidence = 0.9.
- Action: "Moderate: Immediate Repairs Required for Moderate Large Cracks."

2. Radiation Risk Rule:

- **Input**: Radiation level = 10.0 mSv, confidence = 0.7.
- Action: "Moderate: Monitor and Mitigate Radiation Risks."

TABLE I
FORWARD CHAINING TEST RESULTS

Test Case	Input Conditions	Inferred Action
Crack	Crack width = 15.0	Moderate: Immediate
Severity	cm, $conf = 0.9$	Repairs Required
Radiation Risk	Radiation level = 10.0 mSv, conf = 0.7	Moderate: Monitor and Mitigate Radiation Risks
Hazardous Zone Proximity	Hazardous zone = True, conf = 0.8	Critical: Reconstruction Delayed

B. Backward Chaining Results

Backward chaining was tested to evaluate the system's ability to verify whether a specific action could be justified based on the available conditions.

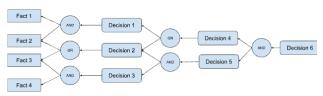


Fig. 5. Backward chaining flow chart [18].

Backward chaining process. A goal is set, and the system works backward to verify if conditions required for achieving the goal are satisfied.

• Key results included:

1. Flood Risk Rule:

- Goal: "Moderate: Flood Protection Measures Required."
- Conditions: Distance to flood zone = 300 m,

confidence = 0.6.

• **Result**: Goal achieved based on input conditions.

TABLE II BACKWARD CHAINING TEST RESULTS

Goal Action	Conditions Verified	Outcome
Critical: Reconstruction Delayed	Hazardous zone = True, conf = 0.8	Achieved
Moderate: Flood Protection Measures	Distance to flood zone = 300 m, conf = 0.6	Achieved
Low Priority: Flood Risk is Minimal	Distance > 500 m, conf = 0.4	Achieved

C. Key Observations

- The system successfully handled both individual and combined rules, demonstrating flexibility and scalability.
- 2. Confidence levels played a critical role in scaling the priority of actions, enabling dynamic decision-making.
- 3. Combined rules, such as hazardous zone proximity and radiation risks, showcased the system's ability to process multi-fact scenarios efficiently.

VI. COMMENTS

This section provides an evaluation of the strengths and limitations of the implemented expert system for post-war building assessment. It also discusses potential improvements and scalability for future applications.

A. Strengths

1. Adaptability:

- Rule-based architecture allows the system to be easily modified and expanded to include new rules and conditions specific to different regions or scenarios.
- Fuzzy logic enhances the system's capability to handle uncertainties, making it robust for complex post-war environments [11].

2. Scalability:

• The system can be scaled to process data from multiple buildings or urban areas simultaneously, leveraging modern computational resources [17].

3. Practicality:

- The user interface is intuitive, enabling field engineers and non-expert users to interact with the system effectively.
- The inclusion of confidence levels ensures prioritized actions, optimizing resource allocation during recovery.

B. Limitations

1. Dependence on Domain Knowledge:

- The quality of the system heavily relies on the accuracy and comprehensiveness of the rules in the knowledge base [1], [3].
- Integrating highly specific or region-dependent rules can be challenging without extensive input from local experts.

2. Environmental Context:

• While the system includes rules for hazardous zones, flood risks, and radiation levels, it may need additional refinement to address complex multi-hazard scenarios [7], [10].

3. Computational Efficiency:

 Processing combined rules with high levels of complexity can lead to longer inference times, especially in backward chaining [18].

C. Future Enhancements

1. Integration of Machine Learning:

• Incorporating machine learning models can help refine rules and automatically detect patterns in building damage assessments [2].

2. Data Fusion:

 Combining satellite imagery and IoT sensor data with the current knowledge base can improve the accuracy of assessments [14].

3. Advanced User Interface:

 Developing a mobile version or adding multi-language support can increase the system's accessibility in diverse regions.

VII. CONCLUSION

This study developed a rule-based expert system to assess post-war building conditions in Gaza, addressing the critical need for efficient and reliable reconstruction prioritization. The system combines fuzzy logic and inference mechanisms, enabling it to process uncertainties and provide actionable recommendations for diverse structural and environmental challenges.

The expert system demonstrated its effectiveness in handling both individual and combined rules through forward and backward chaining tests. The results showed that the system could prioritize actions based on confidence levels, ensuring optimal resource allocation for reconstruction efforts. Key contributions include the integration of domain-specific rules addressing hazardous zones, flood risks, and radiation levels, as well as a user-friendly interface for ease of deployment in real-world scenarios.

Despite its strengths, the system is limited by its dependence on domain-specific knowledge and computational constraints when processing highly complex scenarios. Future enhancements could include integrating machine learning techniques for dynamic rule generation, incorporating real-time data from IoT sensors, and expanding the system's capabilities to address multi-hazard scenarios.

In conclusion, this expert system offers a scalable and adaptable solution for post-war reconstruction assessments, contributing to the resilience and recovery of affected communities. Its modular architecture and robust inference mechanisms make it a valuable tool for disaster recovery planning and management.

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