Secure Systems Design and Technology Development. Veliko Tarnovo, Bulgaria
Proceedings of the International Scientific Conference, 2026. Volume III, 99-105

Generalized Net Model of the Disaster Protection Assessment Process Using Artificial Intelligence

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***Abstract*: The paper presents an original generalized net model (GN-model) for using artificial intelligence in assessing the protection of the population and infrastructure in disasters. It includes assessments of basic components such as population, infrastructure, personnel and procedures using intuitionistic fuzzy logic. A simulation of the GN-model was conducted in the GN IDE simulation environment and some of the results obtained are presented. Possible applications of the model for improving the procedures for protecting the population and infrastructure in disasters and accidents are described.**

Keywords: AI, crisis, generalized net, model

I. INTRODUCTION

Managing the protection of the population in disasters and accidents is a major challenge for modern society due to the unexpectedness of the event, the scope of damage, uncertainty, sometimes the inadequacy of the measures taken and, last but not least, the lack of experience. By applying modern technologies and innovative solutions using UAS to obtain information, this process can be significantly facilitated, since traditional algorithms have difficulty dealing with uncertainty, and here artificial intelligence (AI) comes to the rescue for processing large streams of sensor data and for rapid analysis of the situation.

The paper presents an innovative approach to modeling crisis management through a hybrid GN-AI architecture, including the integration of information extraction tools (UASs, satellites, sensors, social networks, etc.), their processing through artificial intelligence (primary data analysis, computer vision for destruction, sensor analysis), modeling through Generalized Nets (GN) and the use of solutions based on large language models (LLM) such as Chat-GPT, Gemini, etc., for semantic interpretation and generation of generalized operational information in natural language to the crisis headquarters.

For a more precise assessment of the characteristics of objects in conditions of uncertainty typical of crisis situations, the use of Intuitionistic Fuzzy Logic (IFL) is proposed, which extends Zadeh's fuzzy logic (FL) and allows the use of more parameters for assessment - in addition to the degree of belonging (μ), also the degree of non-belonging (ν) and uncertainty (π). The application of other modeling networks, such as N-nets (a variation of Petri nets), is used in [1]. Other publications related to the modeling and analysis of threats to information systems can be seen in [2, 3, 4].

II. MATERIALS AND METHODS

HYBRID GN-AI ARCHITECTURE TO SUPPORT CRISIS MANAGEMENT

The integration of Generalized Nets (GN) and Artificial Intelligence (AI) through a multi-agent architecture Multi-Agent System (MAS) enables the construction of a dynamic, self-learning system. Specialized AI agents analyze data streams in real time (terrain sensors and drones for seismic activity, use of hydrological and meteorological models for probable floods, etc.), and through prediction algorithms based on the use of Convolutional Neural Networks (CNN), anomalies are identified before they develop into a critical event. In a critical situation, AI agents can optimize travel routes in real time and avoid closed or dangerous evacuation routes. The use of Generalized Nets allows for more flexible modeling of different objects, subjects and resources (teams, population, infrastructure, logistics, etc.) because they can integrate different tools (methods, algorithms, fuzzy evaluation functions, etc.) for more precise modeling. GN can be presented as the backbone of such a hybrid architecture for modeling the process, including the following components:

1. Perception Layer (AI)

The use of CNN for real-time camera image analysis (identification of destroyed infrastructure) is important for predicting possible threats to the population, as they automate the "vision" of drones, transforming the visual stream into specific information about the damage [5].

Online ISSN 3044-7771
https://doi.org/10.68302/std2026.vol3.142

CNNs support the process of identifying damaged infrastructure in the following ways:

1) Automated recognition of specific defects

CNNs are designed to recognize visual patterns (edges, shapes, and textures) in a manner similar to human vision, but at much higher speed [6]. Models such as YOLO (You Only Look Once) can identify cracks in concrete, exposed reinforcement, or missing elements of bridges and buildings in real time [7]. CNNs can perform damage classification by degree (e.g., from slight surface defects to complete structural collapse), which helps prioritize rescue operations [8].

2) Real-time analysis

Integrating optimized CNN models directly into drone hardware allows data to be processed on-site (Edge computing) instead of waiting for data to be transmitted to a central server [9]. This is achieved with traffic mapping: drones can immediately mark blocked roads or collapsed bridges on a virtual map of the area, guiding rescue teams along safe routes. Speed of response is also important: AI models achieve accuracy of over 90-95%, processing thousands of frames in minutes – a task that would take a human team hours [10].

3) Semantic terrain segmentation

Unlike simple object detection, architectures such as U-Net or SegNet perform terrain segmentation pixel by pixel. This means that AI can accurately delineate the boundaries of flooded areas or the area of collapsed buildings, which is very useful for timely calculation of the necessary resources for restoration [11].

4) Threat detection in adverse conditions

CNNs can be combined with various sensors (thermal cameras, LiDAR) to see through smoke or at night. This allows thermal analysis to identify structural damage through temperature anomalies (e.g. hot water leaks or short circuits), as well as to ignore "noise" – well-trained neural networks can distinguish a crack in concrete from ordinary shadow or vegetation, avoiding false alarms [12].

The integration of CNNs into generalized nets allows for great scalability – hundreds of drones can simultaneously scan a huge area, with each agent (MAS) sending only the most important information about critical damage to the crisis center.

2. Natural Language Processing (NLP)

In disaster situations, the flow of information from social networks and telephone lines is huge and chaotic. NLP for analyzing signals from citizens and social networks turns this chaos into structured data. NLP technologies serve to filter and structure informal communication from the population by automating text analysis (social networks, SMS, chatbots) to extract critical data about the location and type of incident, which allows MAS agents to reallocate resources to the hottest spots in real time. Some of these capabilities are as follows:

1) Automatic classification of NLP models, such as BERT or RoBERTa – allows for quick recognition of the type of incident in a text message (e.g. "fallen person", "flood", "fire"). This allows the system to automatically prioritize some incidents over others and direct specialized teams according to the specific situation. A study on how transformation models (BERT) filter out the "noise" in social networks to extract only emergency signals can be found in [13] and [14].

2) Named Entity Recognition (NER) – the algorithms allow the extraction of named objects and recognize names of streets, neighborhoods or landmarks in informal texts (e.g. "near "Eagle Bridge"). This allows the automatic mapping of signals on the map, even in cases where GPS coordinates are not sent [15].

3) Sentiment Analysis and Panic Detection (Sentiment Analysis) – by analyzing the emotional charge of messages, authorities can identify outbreaks of disinformation. This helps to direct psychological support teams or send refuting messages to calm the population [16].

4) Summarization – a very important task that AI can easily handle if there are thousands of tweets or posts published about a single event. In this case, NLP models create a short summary for operators: "The bridge in the north is impassable, over 200 people are reporting it." This saves time for dispatchers, who do not have to read thousands of individual messages [17].

3. Decision Layer

One possibility to support decision-making in crisis situations is to use AI agents for dynamic resource allocation through Reinforcement Learning (RL). Here, the agent is trained to allocate resources (personnel, rescue teams) in a simulation environment. In this training, the AI agent makes a series of decisions in a dynamic simulation environment through a mechanism of "rewards and punishments". In the context of crisis management, this approach is used to optimize logistics and the allocation of critical personnel in real time [18]. Unlike traditional static algorithms, RL agents can navigate complex scenarios with high uncertainty, adapting to sudden changes in the infrastructure to minimize response time [19].

Another possibility is the application of Intuitionistic Fuzzy Logic (IFL) in the management of generalized nets, where it is a natural extension of the Theory of Generalized Nets, developed by Acad. Atanassov. Unlike standard fuzzy logic, IFL takes into account not only the degree of membership (μ), but also the degree of non-membership (ν) and uncertainty (π), which is critical in the situation of unexpected disasters (e.g. "we are not sure if this road is destroyed").

The application of IFL in the predicates of the transitions of generalized nets is not new, but it allows modeling of situations with a high degree of uncertainty and uncertainty, characteristic of natural disasters [20]. While standard fuzzy logic takes into account only the degree of truth, IFL introduces additional parameters for the degree of falsehood and the degree of fluctuation (volatility) [21]. Within a GN, these logical predicates serve as "intelligent filters" that assess the reliability of incoming information from sensors and citizens, making critical decisions to redirect resources even in the presence of contradictory or incomplete data [22].

4. Execution Layer

The execution layer (evacuation and protection procedures) represents the final phase in the architecture of the multi-agent system, where the decisions made are translated into physical actions to protect the population. Within the framework of the generalized net process modeling, this layer coordinates the work of autonomous evacuation agents that guide citizens along dynamically calculated safe routes (focusing on emergency evacuation path planning, which is the core of the "Execution Layer") [23]. The effectiveness of the evacuation is ensured by real-time data integration, which allows the execution mechanisms to avoid high-risk areas and infrastructure damage. In this regard, [24] presents a mathematical model of how agents simulate and execute evacuation in an urban environment. This layer encompasses both digital early warning systems and the physical deployment of resources to limit the consequences of the disaster. [25] discusses collaborative governance and how decisions are assigned to executive units.

Description of the GN model with AI components

The generalized net structures the overall process, and the AI modules and IFL are integrated into the network and determine the values in the transition matrices. Tokens are not just data, but objects, subjects, resources, infrastructure, procedures, etc., with characteristics (embedding vectors), which are filled in by the data received from sensors after processing by AI modules. The predicates in the transitions are not fixed logical conditions, but results of neural networks (for example: "If the probability of a dam collapse is > 40%, direct the token to an alternative route").

The GN model is characterized by the use of dynamic characteristics, i.e. the AI module acts as a function for updating the characteristics of certain tokens. Each time they pass through a corresponding transition, the AI module "adds" new information to the token's memory. The model also includes a Learning Loop so that the results (success/failure) can be fed back to the AI module for further training (Feedback loop), which makes the GN model more adaptive.

Components with AI integration include:

a) Infrastructure Component (AI for computer vision)

Here, the GN model receives data from sensors and cameras. The role of AI is to use pretrained models (e.g. YOLO or ResNet) for image segmentation. The transition in the GN model analyzes the state of critical infrastructure (roads, hydroelectric power plants, power grid). If the AI detects an anomaly, the Infrastructure token changes its characteristic to Compromised, which automatically triggers resource redirection in the next transition (through the corresponding predicate rules).

b) "Personnel" component (AI for optimization)

Here, AI is used to solve tasks such as "Resource Allocation", and Reinforcement Learning (RL) or Genetic Algorithms can be used for this purpose. When a "Disaster" call arrives, the AI module calculates the optimal number of teams and their composition (doctors, firefighters, engineers) based on the complexity of the situation. The model monitors the workload of the staff in real time (according to the assigned tasks) to prevent fatigue.

c) "Procedures" component (AI for decision-making support)

Here, the role of AI is to support the decision-making process with incomplete information using IFL. The predicates in the matrix are not hard (0 or 1), but depend on membership and non-membership functions (e.g. "the water level is high", "the wind speed is critical"). This component decides which procedure from the "Protection Plans" to activate, with AI assessing the risk and selecting the appropriate procedure (evacuation, isolation or rescue), minimizing potential casualties. The integration of AI and IFL into predicates (so-called Fuzzy Predicates) allows for more accurate assessments by using fuzzy rules, for example: IF (intensity is "High") AND (passability is "Low") THEN (Activate "Air Rescue"). When using IFL, AI models (e.g. neural networks) do not simply provide a classification, but generate IFL values for the characteristics of the token: For example, the AI image analysis module (CNN) scans drone footage and assigns the corresponding token a score (0.7, 0.2) for a given bridge (70% probability of being healthy, 20% of being collapsed, 10% ambiguity due to smoke/clouds). The AI population analysis module analyzes population density and cell data to determine the severity of the situation in a given sector.

Description of GN transitions

The schematic of the model implemented with the generalized GN net is shown in Fig. 1, and the description is as follows:

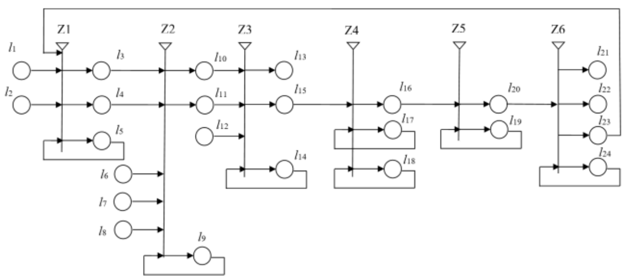

Fig. 1. GN-model of the disaster protection assessment process using AI

GN = {Z1, Z2, Z3, Z4, Z5, Z6}

The model kernels (tokens) used in a generalized net GN are:

• Token α_S (Sensor Data): Initial feature: "raw terrain data" (signals, images, river levels, etc.). AI converts this into "disaster intensity".

• Token α_I (Infrastructure): Feature (μ_i, ν_i) – degree of functionality and degree of destruction of roads/facilities – bridges, hospitals).

• Token α_P (Rescue Team Personnel/Resources): Feature (μ_c, ν_c) – response capacity and degree of exhaustion/risk (also "availability, location and capacity of rescue teams").

• Token α_D (Decision/Actions): Generated in the simulation process as the final result (action plan).

• Token α_{Pop} (Population/People in distress): Feature (μ_p, ν_p) – degree of threat and safety. Example: (0.7, 0.2) means a highly endangered population with 20% certainty in their survival and 10% complete uncertainty (information deficit).

As can be seen, each token carries an IFL score of the type (μ, ν), where $\mu+\nu \leqslant 1$, as well as specific characteristics that are updated when passing through the transitions. When the transitions in the GN-model function using IFL predicates, each transition is triggered if the "degree of truth" for the incoming token exceeds a certain threshold. Below, only the more essential elements of the GN-model will be described – positions occupied by the tokens and predicates used.

Transition Z1: Intelligent perception (Perception Layer)

Here, AI modules process the raw data. The processing is carried out using classical algorithms for computer vision and pattern recognition. At the input positions, tokens αs with terrain data received from sensors located on the site (at position l_1) or from specialized UASs (at position l_2) arrive. The transition matrix contains predicates whose values are generated by AI. Neural networks analyze the flow of tokens and as a result, the tokens receive initial IFL estimates, for example: if AI "sees" smoke, but is not sure whether it is fire, it assigns a high uncertainty π, according to IFL.

Transition Z2: Risk Assessment Layer

This is the most important transition, where the needs of the population and the possibilities for providing assistance meet. It includes the tokens α_{Pop} (population, people in distress), α_I (infrastructure), α_P (rescue teams, resources) and α_S (sensor data). Using IFL predicates, the degree of risk (criticality) for people is calculated in relation to the state of the environment and the possibilities for evacuation.

Input positions:

• l_6: Token α_{Pop} (with an IFL criticality degree (μ_p, ν_p))

• l_7: Token α_P (with an IFL capacity degree (μ_c, ν_c))

• l_8: Token α_I with infrastructure passability data (with an IFL assessment (μ_c, ν_c))

Output positions:

• l_9: for processing and waiting, monitoring (wait)

• l_{10}: for providing assistance on site (relief)

• l_{11}: for active evacuation (evac)

Predicate $W_{9,11}$: „Need for immediate evacuation". $W_{9,11}$ is true if the AI population threat estimate $\mu(\alpha_{Pop})>$ 0.7 and the uncertainty $\pi(\alpha_{Pop}) < 0.2$. If the predicate is true, the toque α_{Pop} moves to the "Evacuation" position (l_{11}).

Transition matrix:

$$r_2 = \begin{array}{c|ccc} & l_9 & l_{10} & l_{11} \\ \hline l_3 & W_{3,9} & False & False \\ l_4 & W_{4,9} & False & False \\ l_6 & W_{6,9} & W_{6,10} & W_{6,11} \\ l_7 & W_{7,9} & W_{7,10} & W_{7,11} \\ l_8 & W_{8,9} & W_{8,10} & W_{8,11} \\ l_9 & W_{9,9} & W_{9,10} & W_{9,11} \end{array}$$

Predicates (calculated by AI and IFL):

• $W_{3,9}$ and $W_{4,9}$ "If the AI analysis of the token with sensor data μ_S obtained from Z1 requires "processing" in transition Z2".

• $W_{6,9}$ and $W_{6,10}$ "If the AI analysis of the population μpop requires "waiting" (for $W_{6,9}$) or "providing assistance on site" (for $W_{6,10}$).

• $W_{6,11}$: "If the AI population threat assessment $\mu_P>0.8$ and the uncertainty $\pi_P<0.15$" (there is a critical need for evacuation).

• $W_{7,9}$ and $W_{7,10}$ "If the staff capacity μ_c requires "waiting" (for $W_{7,9}$) or "providing assistance on site" (for $W_{7,10}$).

• $W_{7,11}$: "If the staff capacity μ_c allows for transportation".

• $W_{8.9}$ and $W_{8.10}$ "If the AI analysis of the infrastructure μ_{infra} requires "wait" (for $W_{8.9}$) or "provide on-site assistance" (for $W_{8.10}$).

• $W_{8.11}$: "If the AI analysis of the population μ_{pop} confirms a safe route".

• $W_{9.9}$, $W_{9.10}$ and $W_{9.11}$ "If the AI analysis requires "wait" (for $W_{9.9}$), "provide on-site assistance" (for $W_{9.10}$) or "active evacuation" (for $W_{9.11}$) respectively (processing process).

Transition Z3: Resource and infrastructure analysis (Intelligent Analysis Layer)

Here it is decided which resources are fit for use.

The AI component includes a neural network (e.g. CNN) that analyzes data from α_I and α_P to determine the probability of survival of infrastructure objects. The input positions are l_{10} (infra_status) – infrastructure status, l_{11} (staff_status), l_{12} (staff_input) – increase in rescue teams and l_{14} (process) – processing information about the situation, and the output positions are l_{13} – terminal position for failed tokens and l_{15} – transition position for admitted tokens to the next transitions.

The main predicates are the following:

• $W_{10,15}$ (road_ok): "The road is passable for heavy equipment" (result of AI analysis of satellite images).

• $W_{11,15}$ (staff_ready): "The team is in combat readiness" (fatigue/logistics forecast model).

Transition Z4 Aid distribution Layer

When passing through this transition, the tokens acquire new characteristics through the IFL evaluation operator, such as: The population token (α_{Pop}) acquires a new characteristic $F=(\mu_{new}, \nu_{new})$, where μ_{new} is the degree of successful aid distribution (removal from danger).

The AI module calculates the fluctuation index $\pi=1-(\mu+\nu)$. If π is too high (e.g. above 0.4), the model automatically generates a token-request for "Additional Air Reconnaissance" (via position l_{23} of transition Z6). In this transition, α_{Pop} (affected population) α_P (personnel) and α_I (infrastructure) meet, and an optimization algorithm (e.g. Genetic) that works with IFL weights can be used. This allows the rescue team to be selected for which the characteristic μ (readiness) is maximized and ν (risk to the team) is minimized.

This transition takes the data from the environment and classifies it.

Input positions: l_{15} (tokens with data).

Output positions: l_{16} – position occupied by tokens that have successfully passed the transition (α_{Pop} with acquired new characteristics), l_{17}(process-risk_low), l_{18}(process-risk_high) – for determining the degree of risk.

Transition matrix:

$$r_4 = \begin{array}{c|ccc} & l_{16} & l_{17} & l_{18} \\ \hline l_{15} & False & True & True \\ l_{17} & W_{17,16} & W_{17,17} & False \\ l_{18} & W_{18,16} & W_{18,17} & W_{18,18} \end{array}$$

where $W_{17,16}$, $W_{17,17}$, $W_{18,16}$, $W_{18,17}$ and $W_{18,18}$ are predicates calculated by the AI risk assessment module.

Transition Z5: Generation of a decision-making procedure (Decision Making Layer)

This transition is the interface between the model and the human operator. It coordinates everything in a single plan. The AI module is an agent that seeks to minimize a loss function (victims, time).

Predicate $W_{16,19}$(refine): "If the uncertainty π is too high". Then the token returns to the beginning of the network (via position l_{23} of transition Z6) to collect additional data (new feature: "needs verification").

Predicate $W_{19,20}$(final): "If the trust index of the DSS system is above the threshold τ (e.g., $\mu - \nu > 0.5$)". Then the token moves on to the next transition Z6 (for preparing a draft order of the crisis center). If successful, the token receives the characteristic: "Evacuation plan along Route X with team Y".

The DSS module may include a knowledge base (protection rules based on legal regulations and past experience), IFL (a mathematical apparatus that compares intuitionistic fuzzy assessments of different plans) and a visualization panel (Dashboard) for visualization of a "Risk Map" with areas of security (μ) and degree of uncertainty (π).

Transition Z6: Cognitive Interface (LLM Layer)

This is the final transition of the model. Here enter the cores carrying processed data from the previous transitions. Digital data is converted into meaningful sentences using LLM (for example, (0.9, 0.05) into "Critical situation in Zone B, immediate evacuation!"). In this transition, a task list is generated for the teams (Step-by-step) and dynamic maps (Heatmaps) can be generated in real time for the monitors in the crisis center.

The LLM is defined as a function of the characteristics of the final token that enters the transition. The transition Z6 accepts the token α_D (Decision) that entered the network from the DSS system through position l_{12}, and the LLM accepts the data from the previous transitions as a context (Prompt) and generates natural language. For each decision in the model, an Intuitionistic Fuzzy Hesitation Index is calculated: $\pi = 1-(\mu+\nu)$. If the LLM finds, for example, that $\pi > 0.4$ (too many unknowns), the model automatically returns the token back to Z1 for "Additional Intelligence" (through position l_{23}) before confirming the evacuation order.

Input for the LLM: IRL estimates from the transitions (μ, ν, π), the state of the "Population" token and the capacity of "Personnel".

LLM Output: Synthesized report like: "In area B there is an 85% risk of flooding, evacuation is difficult due to a collapsed bridge (uncertainty 15%). Recommendation: Air rescue."

Action plan: Outlined steps for rescue teams.

Possible generation of scripts (e.g. in Python) to draw interactive maps in the crisis center.

III. Results and Discussion

Simulation of the GN model in the GN IDE simulation environment

By using the GN IDE (Generalized Nets Integrated Development Environment) simulation environment, different scenarios can be set and how the process is modeled in different crisis situations can be studied. One example of this is reducing the evacuation time and more efficient use of the infrastructure (quantitative indicators) in a specific flood simulation scenario. In this case, the cores enter the input positions of the network (transition Z1) and in the processing process (through position l_5) the AI module supplies data on rising waters. IFL filters the uncertain data received from the sensors and initially processed by the AI module. Further, other cores enter the network for assessing the infrastructure, for personnel (rescuers), etc., and at transition Z5 DSS suggests evacuation routes. The language model (LLM) at transition Z6 prepares a visualization of the data with a media release and an evacuation plan.

Some steps of the model simulation process with GN IDE can be seen in Fig. 2.

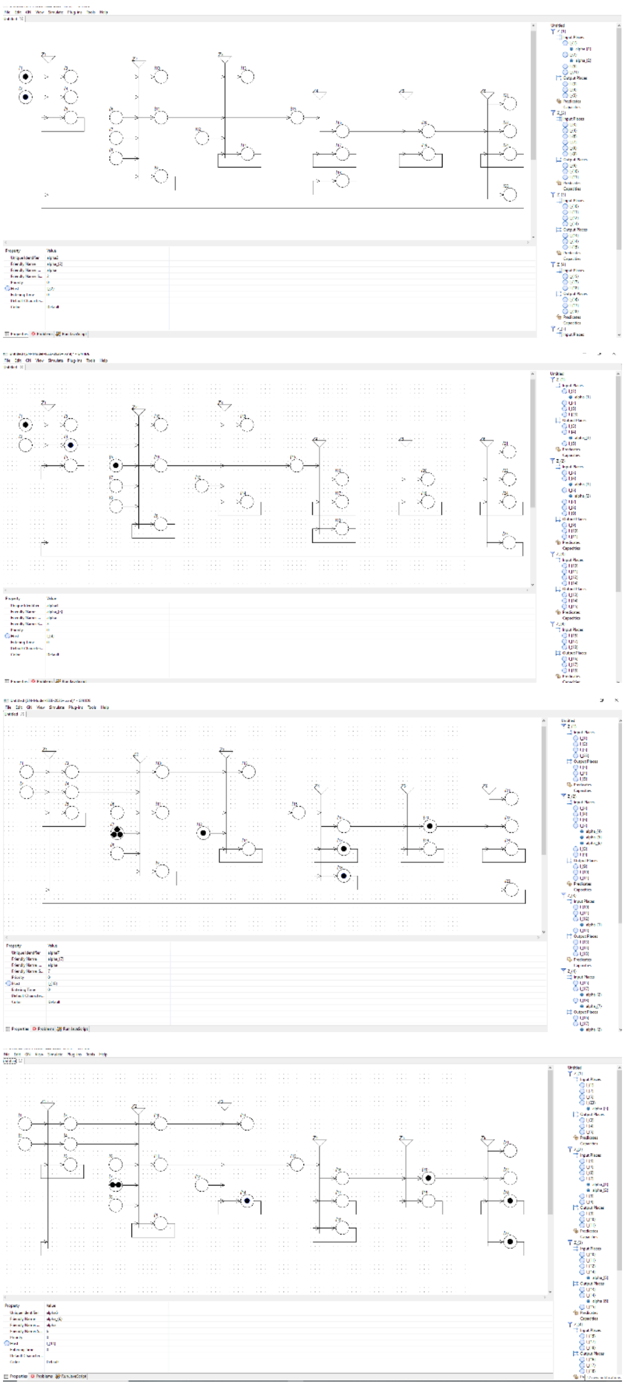

Fig. 2. Screens from the GN model in the GN IDE simulation environment

The application of AI and GN-modeling is increasingly being used in various fields, one of which is national security and defence. This area has been the subject of intensive work in recent years and many scientific studies have been conducted, such as in [26, 27, 28].

IV. Conclusion

The presented original GN-model with AI-support to support the crisis management process is an attempt to expand the application of generalized models in an integrated approach of sensor data (obtained from UASs and from the local area), information processing through AI-modules (agents) and the application of language models (LLM) for communication with the crisis headquarters in natural human language. The use of IFL in the evaluation functions of the tokens that move in the generalized net provides an additional opportunity for more detailed modeling of the data processing process in the presence of uncertain information, which is characteristic of the complex conditions of the crisis situation. An important element is also the attempt to transition from static plans to “Dynamic Procedures”, which are adapted in real time by trained AI-models. This is perhaps the first attempt to integrate Deep Learning into the framework of Generalized Civil Protection Nets, by creating a single methodological framework, combining the rigor of GN with the flexibility of AI and reducing the subjective factor (“human error”) for the initial damage assessment.

V. Acknowledgment

This work was supported by the NSP “Security and defence” program, which has received funding from the Ministry of Education and Science of the Republic of Bulgaria under the grant agreement no. Д01-74/19.05.2022.

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