AI-Based Design of Decision Support Systems for Industrial Risk Management

Andrzej M.J. Skulimowski,[1,2] [0000-0003-0646-2858] Paweł Łydek[1,2] [0000-0001-9077-4998]
[1]AGH University of Science and Technology, Chair of Automatic Control and Robotics, Decision Science Laboratory, 30-059 Kraków, Poland
[2]International Centre for Decision Sciences and Forecasting, Progress & Business Foundation, 30-048 Kraków, Poland
ams@agh.edu.pl, lydek@agh.edu.pl

Abstract. This paper presents a new approach to design intelligent decision support system for industrial risk management. The need for this class of systems has been driven by complex resilience building and action planning problems that occur in large industrial plants. The proposed software architecture of the decision support system (DSS) is AI-based and applies Bayesian, causal and anticipatory networks, as well as multicriteria analysis, expert information fusion and knowledge processing techniques. The use of AI-tools follows the AI-alignment paradigm, where AI evolution is followed to discover most suitable techniques to solve safety-related problems. We propose a general scheme of DSS for risk management that includes threats, sensors, information processing, and decision models. The DSS and risk management module are coupled within a semi-supervised machine learning procedure, where the results of prior decisions serve to learn risk mitigation action parameters and managerial preferences.

Keywords: Intelligent Decision Support Systems, Risk Modelling, Multicriteria Optimization, Semi-Supervised Learning, Information Fusion.

1 Introduction

Risk management is a broad subject which often involves the use of artificial intelligence (AI) and machine learning (ML) methods. It usually focuses on financial risks or cyber threats. This article refers to a real-life case of an intelligent decision support system (DSS) designed for a limestone mine in Poland, where heterogeneous natural and anthropogenic threats can be prevented or mitigated with a wide spectrum of AI-based techniques. The heterogeneous character and high frequency of acquired threat data make it impossible to process all this information solely by human first responder forces in case of emergency. Moreover, while some of the sensor information, such as fire or flood alerts, can be quickly transformed into mitigating actions, other information may be incomprehensible fully or in part for the security staff of the enterprise.

AI methods are also the basis to design the managerial response with the DSS. To deal with complex information and knowledge management problems that should ultimately lead to optimal resolution of risk management issues and minimize the related losses, we propose and construct a causal model of threats, risks, crisis management decisions, and their consequences. The intelligent DSS that incorporates this model is capable of recommending situation-dependent risk mitigation actions, operations, and strategies to ensure an optimal level of industrial safety. Such systems will be termed industrial risk management DSS or disaster resilience management DSS (IRM DSS or DReMSS [8]). The ultimate model should be implemented in an IRM DSS that can support decisions at all relevant levels, from immediate remedies to planning complex operations and long-term strategic resilience-building measures. The system is developed according to the DevOps paradigm, while experience learned with its operations is additionally enhanced by links to external AI-foresight and AI-alignment modules. These support the future-oriented development of the next IRM DSS releases. The AI techniques are applied primarily to sensor information processing and fusion, design of intelligent multicriteria DSS and ML procedures. Optimal decisions are derived with the core decision support engine that processes all threat-related information available, such as sensor data, historical facts on past threats, and the ways and results of their handling. The constraints on the decision rules are imposed by law or by internal regulations in the industrial plant concerned.

In the industrial security problems considered in this paper, risk is attributed to external threats, to information processing procedures that can bias the data with errors, to human operational errors, and to systematic erroneous decisions that can be made during risk management. For example, temperature measurement in fire sensors can be biased by the inaccuracy of thermometers, which can be assessed in advance as ex-ante measurement error. If the uncertainty is too high, the information from additional remote infrared sensors can be fused to yield trustworthy risk assessment.

The general threat transfer will be modelled as a network, where incidental operational and decision-making faults are sources of additional risks. This network is complemented by the risk management and optimization model involving decision algorithms, actions, and actuators. Both components of the model are coupled by feedback information received by the sensors, compared to the values provided by the model and presented to the ML module and to the decision makers. The DSS engine uses the above model components sequentially and links them to a semi-supervised machine learning procedure, where the assessments of previous decisions serve to learn sensor characteristics, risk mitigation procedure parameters, and managerial preferences.

2 Real-Life Needs And Related Research Inspiration

Limestone mining is related to specific risks caused by the occurrence of phenomena such as landslides or rock falls in multiple locations distributed over a large area. Such phenomena result from heavy machine traffic, shooting work, or from natural causes such as heavy rain or snowfall. Therefore, safety management systems implemented in an opencast mine should ensure a periodic inspection of the mining area in order to identify potential threats. Due to the nature of the business, i.e. working on a vast and rapidly expanding area, physical securing of operations with fences or human patrolling are practically impossible. The motivation for applying advanced AI information processing methods and software originates from the fact that the above challenge can be satisfactorily met by AI-based monitoring and prevention technologies. These include visual monitoring cameras, radars, lidars, and other sensors installed on autonomous ground-based or aerial inspection robots. The ML-based automatic interpretation of images from the protected area will indicate sites at risk, e.g. those with displacement of geological structures, where rock is likely to collapse.

While AI is widely used in financial risk management systems, its deployment in natural and anthropogenic crisis management systems was rare until recently [8]. When designing the IRM DSS for the limestone mine that serves as an illustration of our approach, we took into account the current development of crisis management systems with decision support functionalities. This class of DSS emerged from early warning systems that evolved into cloud-based heterogeneous signal processing [1]. Then, various crisis management and DSS architectures were proposed [2]. The diversity of threats and feasible prevention and mitigation measures showed an increased relevance of trust analysis of information sources [6]. The evacuation of staff and equipment turned out to be the most important problem from the point of view of solving the resilience problems in the opencast mine related to natural threats [3]. The hierarchical character of emergency decision making and long-term prevention planning resulted in the adoption of the roadmapping methodology to design the DSS [4].

The main goal of this article is to propose a software architecture that allows decision makers responsible for crisis management to integrate the surveillance, signal processing, and decision support technologies in a holistic industrial security system. The IRM DSS functionalities that require an intensive development of new AI techniques are the fusion of information obtained from various sources in real time and the development of optimal decision algorithms that use this fused information. In addition, machine learning techniques, both reinforcement and supervised learning, enhance the selection of preventive and mitigation measures in emergency situations. A preliminary scheme of the AI-based enterprise threat management system for a limestone mine is presented in the next section. The conclusions are provided in sect. 4.

3 Research Issues In Design Of Industrial Risk Management DSS

We will start this section by presenting a formal background to industrial risk modelling, referring to the real-life problems occurring in an opencast mine as a motivating example. However, we claim that the presented models will be useful in solving a broad family of related industrial risk and safety management problems.

We propose a general model of risk measurement as a network of information processing modules, which includes sensors, information fusion, decision support, and automated decision making nodes. Direct signals from threat and risk measurements serve as input to the DSS and risk management and optimization module. The decision algorithms identify potential best-compromise actions and actuators to implement them, and the DSS proposes the outcomes to the decision makers. For the aims of the present study, we assume that the risk model features the following objects:

- multiple threats, natural or anthropogenic,
- two types of information fusion nodes: these capable of fusing information of the same kind from different sensors (simple fusion), and complex fusion nodes capable of processing heterogeneous information,
- endangered humans, whilst dangers can face their health or life,

- artefacts-at-risk, such as machines, vehicles, buildings etc.; threat propagation is depicted as a subgraph of the overall multigraph,
- lower, middle, and top-level decision units, artificial or human,
- rescue teams, robots, actuators (such as extinguishers) that all implement emergency management decisions; for the sake of brevity termed ‘responders’,
- additional resources that can be used as responders by the enterprise crisis management when necessary.

The model objects and relations between them form a dynamic directed multigraph, with three types of edges that denote information flow, threat propagation and impact, and decision transmission and impact (deontic structure). In the next step, this basic multigraph will be extended with auxiliary structures, such as production line schemes, where a threat imposed on a predecessor causes production interruptions at a subsequent nexus. To make possible application of ML methods and emergency management based on quantitative analysis, the following rules should apply:

- Several information sources reporting the same threat should be adjacent to an information fusion node.
- The information flows are labelled with information credibility coefficients [5].
- There is an information flow path from each information source and each information fusion node to a decision node.
- Each responder is linked by an incoming path to at least one decision node.
- Decision nodes, decisions transferred to lower-level units, rescue teams and actuators, as well as feedback information on their consequences, form a hybrid anticipatory network [7], so that each decision unit is linked to a top-level unit.

A general functional scheme of IRM DSS applicable to a broad class of industries is shown in Fig. 1. This type of diagram will be termed *threat-risk-response map*.

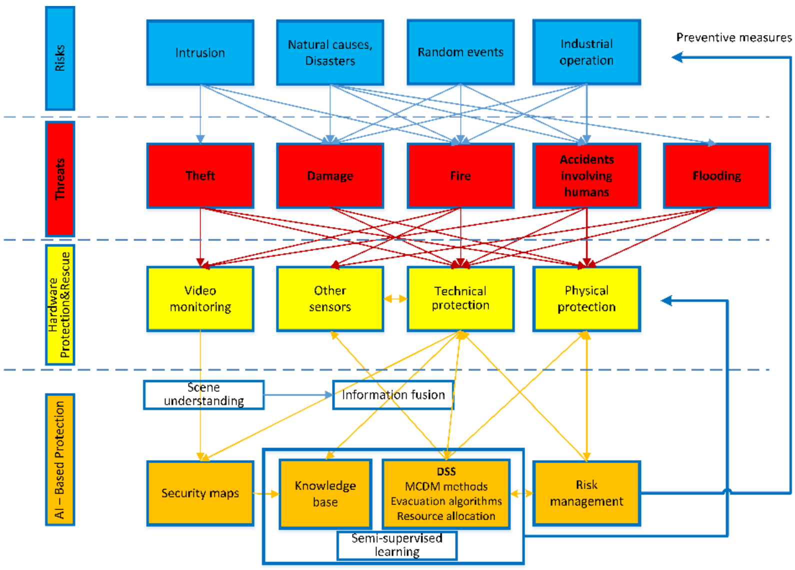

Fig. 1. An example of threats, sensors, information fusion units, and decision making network.

4 Concluding Remarks

In case of emergency, intelligent IRM DSSs will be used sequentially within a semi-supervised ML procedure, where the threat, prior decisions and their outcomes stored in the knowledge base are used to learn current risk mitigation and prevention parameters. The design of an IRM DSS for a limestone mine is a typical system deployment in large industrial area. It showed the benefits of using AI methods such as information fusion, semi-supervised and reinforcement learning, and image understanding to increase risk management capabilities and efficiency. The proposed AI-based DSS design approach can provide viable implementations capable of solving heterogeneous industrial threat management problems in various industries in real time. The IRM-DSS architecture ensures simultaneous optimization of safety management criteria defined in the organization's safety assurance strategy and economic indicators.

Further research on AI-based risk assessment and mitigation in large industrial plants will be focused on the analysis and selection of decision support methods, and new DSS architectures. The specificity of threats and risks will require more penetrative risk modelling and risk response with specific preventive and mitigation actions., If there is a need to manage natural hazards with own forces in large industrial areas, it is necessary to provide both, appropriate instruments and decision-making procedures. We argue that they all can be implemented as a holistic IRM-DSS.

References

1. Chen, D., Liu, Z., Wang, L., Dou, M., Chen, J., Li, H.: Natural disaster monitoring with wireless sensor networks: A case study of data-intensive applications upon low-cost scalable systems, Mobile Netw. Appl. 18(5), 651–663 (2013), doi:10.1007/s11036-013-0456-9.
2. Domdouzis, K.: Artificial-intelligence-based service-oriented architectures (SOAs) for crisis management. In: Handbook of Research on Investigations in Artificial Life Research and Development, pp. 79–95, IGI (2018), https://doi.org/10.4018/978-1-5225-5396-0.ch005.
3. Ibrahim, A.M., Venkat, I., Subramanian, K.G., Khader, A.T., De Wilde, P.: Intelligent Evacuation Management Systems: A Review. ACM Trans. Intell. Syst. Technol. 7, Art. No. 36, p. 27 (2016), https://doi.org/10.1145/2842630.
4. Kerr, C., Phaal, R.: Technology roadmapping: Industrial roots, forgotten history and unknown origins. Technol. Forecast. Soc. Change 155, Art. No. 119967, p.16 (2020).
5. Moyano, F., Fernandez-Gago, C., Lopez, J.: A Conceptual Framework for Trust Models, Trust, Privacy and Security in Digital Business, Lecture Notes in Computer Science 7449, Springer-Verlag, Berlin-Heidelberg, pp. 93-104 (2012).
6. Skulimowski, A.M.J.: Universal intelligence, creativity, and trust in emerging global expert systems. In: L. Rutkowski et al. (eds.), Artificial Intelligence and Soft Computing. ICAISC 2013, Proceedings. Lecture Notes in Artificial Intelligence 7895, Springer-Verlag, Berlin–Heidelberg, pp. 582-592 (2013), https://doi.org/10.1007/978-3-642-38610-7_53.
7. Skulimowski, A.M.J.: Anticipatory Network Models of Multicriteria Decision-Making Processes. Int. J. Systems Sci. 45(1), 39-59 (2014), doi:10.1080/00207721.2012.670308.
8. Skulimowski, A.M.J., Bañuls, V.A.: AI Alignment of Disaster Resilience Management Support Systems. In: Rutkowski L. et al. (eds), Artificial Intelligence and Soft Computing. ICAISC 2021. Lecture Notes in Artificial Intelligence 12855, Springer, pp. 354-366 (2021), https://doi.org/10.1007/978-3-030-87897-9_32.