

Hybrid AI Model for Proportionality Assessment in Military Operations

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Abstract: In recent years, Artificial Intelligence (AI) has revolutionized the military domain and in particular the planning, execution, and assessment of military operations, leading to the development of advanced decision support systems. In this context, this research introduces a novel hybrid AI model for proportionality assessment in military operations, merging the advantages of artificial neural networks with fuzzy logic to create a robust and adaptable system. This approach combines the learning capabilities and pattern recognition strengths of neural networks with the ability of fuzzy logic to handle uncertainty and linguistic variables. In this way, the model addresses the complex challenge of estimating collateral damage and military advantage in dynamic operational environments and further proposes proportionality assessment decisions. Experimental results demonstrate that this intelligent approach contributes to existing models in both accuracy and explainability terms. Moreover, the model is adaptable to diverse scenarios and provides clear, interpretable results, aspects that are crucial for military decision-makers. By bridging the gap between data-driven learning and expert knowledge representation, this research contributes to the development of more ethical and legally compliant AI solutions for military operations, particularly in the critical domain of proportionality assessment in targeting decisions.

Keywords: Targeting, Proportionality, Military operations, Neuro-fuzzy, Hybrid AI, Artificial intelligence

1. Introduction

"Intelligence is the ability to adapt to change."

(Stephen Hawking)

Military targeting is a process that finds itself in a central position when conducting military operations. This process involves the systematic selection and prioritization of targets, followed by the application of appropriate responses, taking into account strategic and operational requirements together with available capabilities (NATO, 2016; US Army, 2013). This process has a multidisciplinary nature, requiring seamless coordination and integration of various experts, specialties, and capabilities. Timeliness is crucial, often necessitating rapid up-to-date information flows to address time-critical targets. To maintain operational cohesion, the targeting process is centrally coordinated. Furthermore, the accessibility and security of critical information, such as target intelligence and collateral damage estimates, require robust (intelligent and adaptive) systems for storage, retrieval, and dissemination at various stages of the operation. This comprehensive approach ensures that military targeting efforts are precise, effective, and aligned with broader strategic objectives (NATO, 2016).

The military targeting process is fundamentally governed by legal frameworks and ethical considerations. This implies direct compliance with the laws of war, also known as International Humanitarian Law (IHL) or the Law of Armed Conflict (LOAC), which serves as the cornerstone for conducting targeting operations and making targeting decisions together with the Rules of Engagement (RoEs) defined and applicable per military operation (CLAMO, 2000). These laws, which have evolved through international treaties, customary practices, and judicial decisions, establish the parameters within which the military forces must operate during armed conflicts. They aim to balance military necessity with humanitarian considerations, prohibiting certain types of targets, weapons, and tactics while mandating precautions to minimize collateral damage (ICRC, 2024). Adherence to this legal framework is both a moral imperative and a practical necessity which ensures that targeting decisions are legally defensible, strategically compliant, and take into account ethical considerations.

A fundamental principle in the conduct of military operations is the principle of proportionality. This principle states that an attack than can "cause incidental loss of civilian life, injury to civilians, damage to civilian objects, or a combination thereof, which would be excessive in relation to the concrete and direct military advantage anticipated" is disproportional (AP I Art.51(5)(b), 1977). This requires military commanders to balance the anticipated military advantage of an attack against the expected incidental harm to civilians and civilian objects. In other words, attacks that may cause excessive civilian casualties or damage in relation to the concrete and direct military advantage anticipated should be prohibited (Gill & Fleck, 2011; Boothby, 2012;

Dinstein, 2016). While essential for protecting civilians, the principle's practical implementation can be challenging for military commanders, requiring complex real-time decision-making based on available intelligence and the anticipated outcomes of an attack. Modelling the proportionality assessment in military operations requires the development of intelligent and adaptive up-to-date models that can effectively capture the complex interplay between collateral damage and military advantage. These models must incorporate intelligent adaptive algorithms capable of processing real-time data from sources such as civilian presence, infrastructure vulnerability, and potential cascading effects of attacks. At the same time, these should integrate dynamic assessments of military objectives, tactical significance, and strategic outcomes to quantify the anticipated military advantage. In addition to these elements, the system also needs to embed and implement the "excessive" relationship between collateral damage and military advantage, a mysterious concept that implies subjectivity, context dependency, and is surrounded by uncertainty.

In recent years, the integration of Artificial Intelligence (AI) in the military domain has increased, with numerous countries investing heavily in AI-powered defence technologies (Jeon et al., 2024; Saigal, 2024). This provides several significant advantages as AI can support and enhance decision-making processes by quickly analysing vast amounts of complex data, potentially leading to more effective and precise operations with reduced collateral damage. Additionally, AI can improve operational capacity in uncertain conditions and enable faster response times, which are crucial in military contexts (Schwartz et al., 2020; Szabadföldi, 2021; Rettore, 2023). Some applications include AI-based intelligence gathering, predictive maintenance of military equipment, and autonomous navigation systems for unmanned vehicles. Nevertheless, while these advancements offer substantial benefits, they also raise important ethical, legal, and security concerns (Schraagen, 2023) that necessitate careful consideration and collaboration to ensure responsible and trustworthy development and deployment of AI in military applications. A powerful AI mechanism that combines the strengths of Artificial Neural Networks and Fuzzy Logic, has emerged as a powerful technique with significant applications in both societal and military domains. This integration benefits from the learning capabilities of neural networks with the human-like reasoning and interpretability of fuzzy systems, resulting in a robust framework for handling complex, non-linear problems. In particular, in the military domain, this hybrid AI mechanism demonstrated valuable results in various applications, including autonomous systems, decision support, and intelligence analysis (Bozanic et al., 2021; Mehrabi, Scaioni & Previtali, 2023; Hagos & Rawat, 2024). Due to its capability of adaptation and its explainable nature, this approach is well-suited for the dynamic and complex environments encountered in military operations and is able to tackle complex assessment processes such as the one based on the principle of proportionality.

Therefore, this research aims to develop a hybrid AI model designed to implement the proportionality assessment in military operations, addressing the central research question: "How to build a hybrid AI model for assessing proportionality in military operations?" To achieve this objective, a multidisciplinary stance is adopted by integrating concepts, methodologies, and techniques from the fields of military science, military law, and AI. By synthesizing knowledge from these diverse domains, the goal is to create a comprehensive framework that can effectively analyse and evaluate the complex factors involved in determining proportionality within the context of military decision-making and operational planning. It does that adopting the neuro-fuzzy paradigm and building on previous research conducted in this domain. Through this effort, this research further aims to contribute to the development and use of more responsible and trustworthy AI-based systems in the military domain.

The remainder of this article is structured as follows. The second section of the article discusses relevant studies related to the applicability of neuro-fuzzy and in particular, the ANFIS technique, in the military domain. At the same time, a summary of the functional mechanism of the ANFIS technique used in this research is provided. Section 3 presents the methodological approach considered in this research in order to obtain the goal established. Section 4 discusses the implementation choices during the modelling process and the results obtained. At the end, Section 5 provides concluding remarks and future research perspectives that could be considered in this domain.

2. Research Background

A neuro-fuzzy modelling approach implies the fusion between Artificial Neural Networks and Fuzzy Logic AI techniques where benefits from the learning capabilities of ANN are brought together with the human-like reasoning that fuzzy systems have. These hybrid intelligent systems are broadly used in various societal domains due to their ability to handle dynamic, complex, and nonlinear problems while maintaining interpretability, a fundamental requirement when building and using AI systems (Maathuis, 2023). Moreover,

the neural network component facilitates adaptive learning from data, while the fuzzy logic component incorporates expert knowledge captured through linguistic rules, enabling the system to handle uncertainty effectively (Bozanic et al., 2021; Talpur et al., 2022). Given their power of adaptation, they represent valuable solutions when other (intelligent) techniques struggle or fail.

A well-known neuro-fuzzy hybrid intelligent system is ANFIS (Adaptive Neuro-Fuzzy Inference System). An ANFIS system transforms the linguistic information and ruling system (i.e., logic rules) represented by fuzzy sets, into analytical values learned through the neural networks algorithms. In addition, when building such a system it is important to account that implementing a high number of rules may have an impact on the effectiveness and interpretability of the system given its distribution of small weights across them. The architecture of the model contains five layers as illustrated in Figure 1: fuzzification layer, rule layer, normalization layer, defuzzification layer, and output layer. In the first layer, the membership degrees to different fuzzy sets are determined for the crisp input values (input x_i). In the second layer, the firing strength is calculated for each fuzzy rule. In the third layer, the firing strengths are normalized. In the fourth layer, the normalized firing strengths and consequence parameters set to compute the defuzzified values. And in the fifth layer, the output of the model is computed through the aggregation of all consequents multiplied by their normalized weights to obtain a crisp output value (output y).

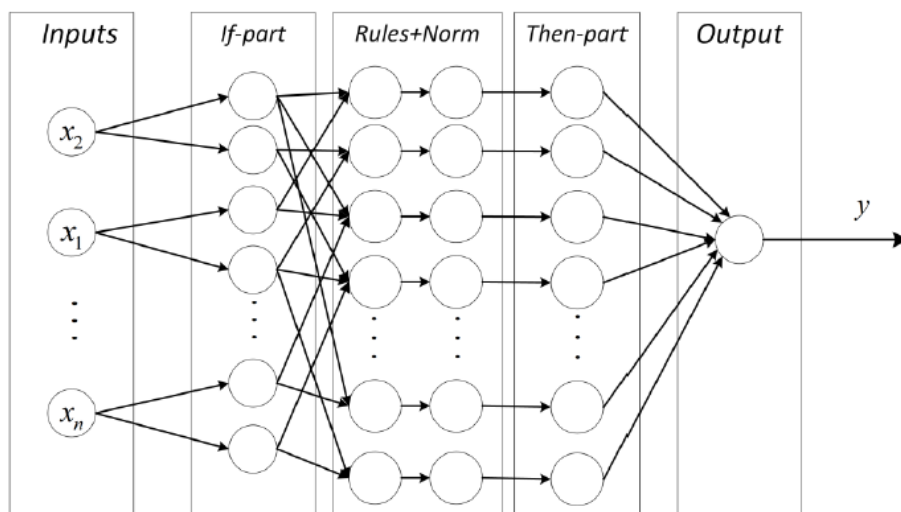


Figure 1: ANFIS model from Zdrorenko et al., (2021) based on (Jang, 1993)

Hybrid AI models have a long history in building various solutions for diverse purposes across various societal domains. Cardullo (1999) proposes a neuro-fuzzy model for understanding how a human operator behaves when compared to an intelligent system. In this process, the human behaviour is represented considering variables that model perceptual, cognitive, and motor processes aspects. Rao, Iliadis & Stefanos Spartalís (2011) propose a neuro-fuzzy model for predicting the impact of weather operations on the effectiveness of air tasking operations and missions. The authors build further an agent-based system that aims at introducing the weather operations in the evaluation of the effectiveness of military mission plans. In the field of aviation, Nuovo et al. (2016) propose a neuro-fuzzy model that leans from data examples collected using a computerized battery for capturing the attention levels of pilots. After assessing the attention performance, the system compares the results against the typical profile of an aviation pilot in order to support existing and future pilot training solutions.

Jain, Yadav & Verma (2020) advance an ANFIS model for cooperative communication in Wireless Sensor Networks (WSN) for reducing the Bit Error Rate (BER) while improving the lifetime of the network. The system considers three clusters of variables (i.e., network topology, radio model, and application) and is implemented in MATLAB. Further, in the context of military information communication networks, Zdrorenko et al., (2021) build an ANFIS model that captures a priori information about the route reliability for making sure that proper decisions are being made before considering specific decisions in the process of transmitting information flows while assuring that the deterioration of QoS (Quality of Service) is avoided in the case of dealing with equipment failures. In this process, the route is calculated in multiple phases that imply obtaining information about the components transmitted in the packet header, calculating the general metrics for the routes available, and deciding on the packets' transmission using a determined path. Yazar, Şöhret & Karakoç (2017)

propose a comparison mechanism for estimation methods dedicated to exhaust gas emissions built for a military engine based on ANFIS. For this method, emissions indexes of carbon monoxide, carbon dioxide, nitrogen oxides, and unburned hydrocarbon are considered as outputs.

In the context of cyber-physical systems, Al-Fetyani, Hayajneh & Alsharkawi (2021) design an ANFIS model as a control system for improving the altitude performance of a quadcopter drone that takes into consideration aerodynamics effects. The model proposed is further tested in various flight conditions that include the capability of rejection of potential external disturbances. Another design-based approach is considered by Selma et al., (2021) when developing an ANFIS model for optimizing the trajectory tracking task of UAVs (Unmanned Aerial Vehicles) based on pigeon-inspired control algorithm optimization. In this way the behaviour of a three-degree of freedom (3-DOF) quadrotor UAV is optimized taking into account its mechanical structure and tracking a given reference trajectory in 2D vertical plane. Farid (2013) proposes an ANFIS-based UAV controller for controlling the lateral position of the UAVs implemented in MATLAB. The results obtained are compared with PID lateral controllers where it can be seen that both models perform well in the given conditions. In the security context, Khalil & Rahman (2023) advance an ANFIS-based Intrusion Detection System (IDS) for assessing and preventing the intrusion of various threats that could affect the sensors of small UAVs through attacks. The solution proposed is successfully evaluated in a hardware-emulated UAV testbed. Mohseni et al., (2022) design an ANFIS regression model for determining the priority of the threat of flying air targets in the context of C2 (Combat and Control) systems in an instant and intelligent manner. The lower rates obtained show the effectiveness of this solution when assessing the threat of flying air targets. At the same time, Goztepe (2013) proposes a military decision-making support for real combat cases of tactical warfare. The solution is further used for military planning support of small units concerning battlefield decisions.

Based on the literature review conducted and the studies discussed above, it can be seen that neuro-fuzzy systems are used in various applications in the military domain, and a significant part of the solutions proposed implement an ANFIS-based model given their capability to adapt to changing environments, integration with other AI techniques, and power to properly represent and automate complex (societal) processes.

3. Research Methodology

This research aims to build a hybrid AI model for performing the proportionality assessment in military operations. On this behalf, the following research question is formulated: How to build a hybrid AI model for assessing proportionality in military operations? In order to be able to achieve this goal, a multidisciplinary research is conducted by merging concepts, methods, and techniques from the military, military law, and AI domains. In this process, the Design Science Research methodology (Kuechler & Vaishnavi, 2012; Peffer, Tuunanen & Niehaves, 2018) is followed and multiple modelling perspectives are considered, as explained in the next section of this article. Accordingly, the following two research phases are executed:

In the first phase, the objective of this research is formulated and the strategy to achieve it is designed. Furthermore, the two components of the proportionality assessment (i.e., collateral damage and military advantage) are defined and structured based on corresponding variables and values of these variables. Accordingly, four different modelling perspectives are considered in relation to the nature of the collateral damage component and the way of applying the classification methodology for the proportionality principle. This research builds on previous efforts proposed by (Maathuis, Pieters & Van den Berg, 2018; Maathuis & Chockalingam, 2023a; Maathuis & Chockalingam, 2023b) and further integrates an extensive literature review into understanding how neuro-fuzzy models are used in the military domain and for assessment processes and decision-making support purposes in general.

In the second phase, given the taxonomy established in the previous phase, the four variants of the model are based on the Neuro-Fuzzy technique and are implemented in Python using the ANFIS library. The resulted model variants are further evaluated with respect to relevant metrics, i.e., accuracy, F1 score, and MSE. The accuracy of the model shows how correct the model is when making predictions by computing the ratio of correct predictions to the total number of predictions made. The F1 score reflects the balance between the precision and recall components while capturing both the false positive and false negative cases. And the MSE metric is used to measure the difference between the predicted and the actual values.

4. Model

Proportionality assessment is a complex process that surrounds the identification of targets and selecting corresponding weapons for engagement by quantifying the anticipated military advantage and estimating potential collateral damage on civilians and civilian objects. This is done by military commanders who must weigh these factors, ensuring that the civilian component is not excessive relative to the military component of the equation. This assessment is refined through consultation with military, military-technical, and military-legal experts to ensure compliance with laws of armed conflict. This implies synthesising all available information, including tactical intelligence, strategic objectives, and legal considerations, to determine whether engaging the target would be proportional and lawful (Henderson & Reece, 2018). This complex process is often conducted under time constraints and represents a critical mechanism for balancing military necessity with humanitarian imperatives in war.

In this research, four perspectives for modelling the proportionality assessment are considered:

- First, where a binary classification stance is taken for assessing if a military operation is proportional or disproportional, and where collateral damage does not include psychological damage.
- Second, where a binary classification stance is taken for assessing if a military operation is proportional or disproportional, and where collateral damage includes psychological damage.
- Third, where a multi-class classification stance is taken for assessing if a military operation is very highly disproportional, highly disproportional, lowly disproportional, or proportional, and where collateral damage does not include psychological damage.
- Fourth, where a multi-class classification stance is taken for assessing if a military operation is very high disproportional, high disproportional, low disproportional, or proportional, and where collateral damage includes psychological damage. A rule example that shows a case of dealing with excessive collateral damage when compared to the military advantage is further considered and presented in equation 1. This implies that engaging such a target is high disproportional (HDP) and should not happen.

$$\text{If } CD_injury \text{ is Low AND } CD_death \text{ is High AND } CD_object \text{ Yes AND } MA \text{ is VL THEN } PA \text{ is HDP} \quad (1)$$

Building on previous efforts in this domain (Maathuis, C., & Chockalingam, 2023a), the models are trained for 13 epochs as illustrated in Figure 2. Learned in this process are, e.g., the membership functions of the collateral damage variable that excludes psychological effects depicted in Figure 3 and the membership functions of the military advantage variable illustrated in Figure 4 below.

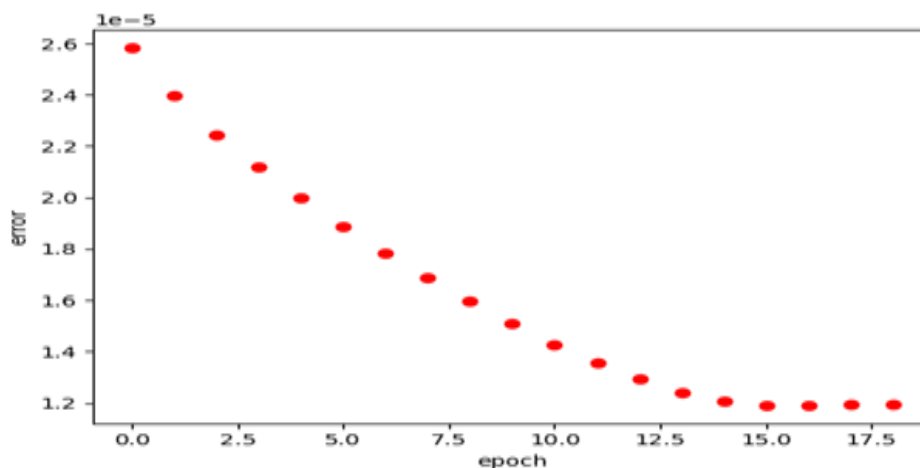


Figure 2: Model training and error capture per epoch

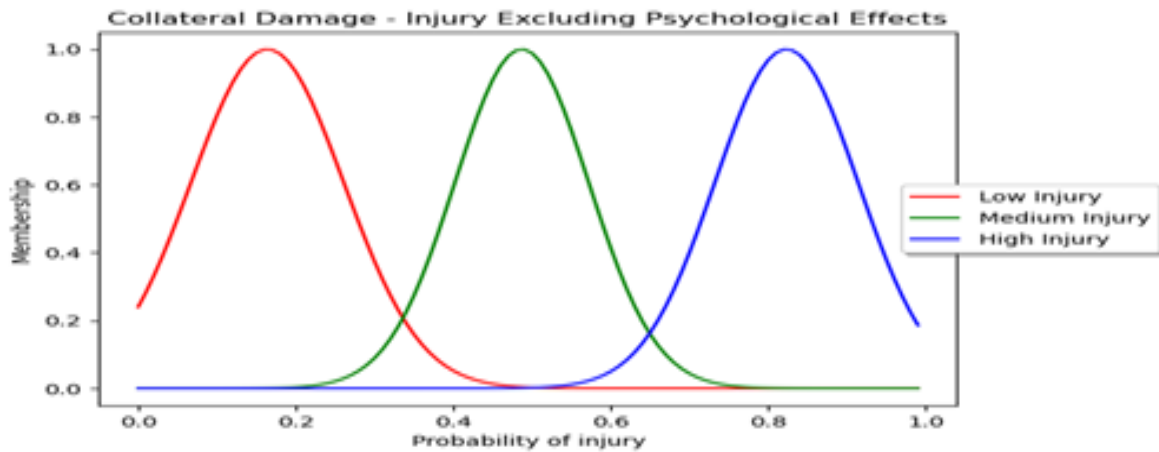


Figure 3: Collateral damage without psychological damage variable

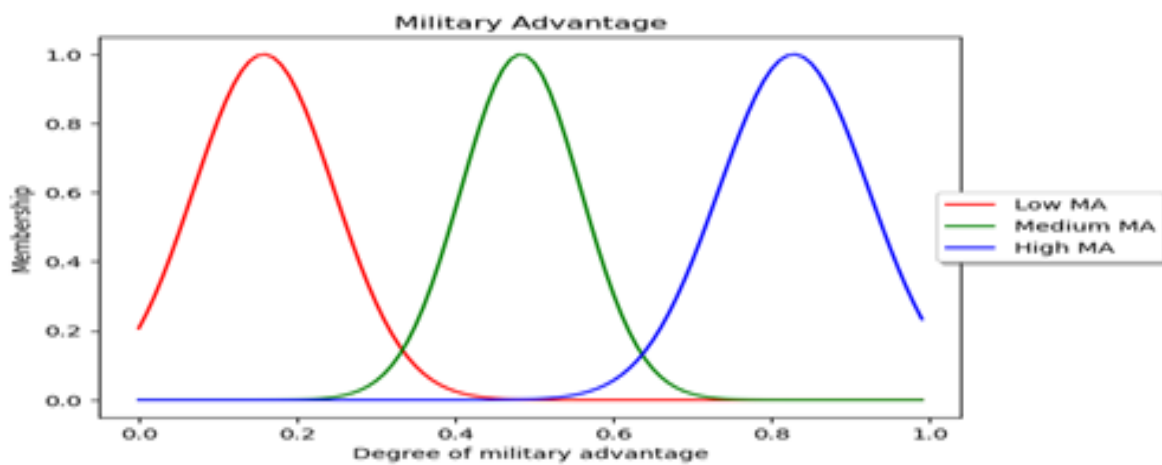


Figure 4: Military advantage variable

For the first two modelling perspectives, the performance of the model shows that the first variant makes more correct predictions than the second model (i.e., accuracy), performs overall better in terms of precision and recall (i.e., F1 score), and has smaller prediction errors on average (i.e., MSE). The corresponding evaluation metrics and values are captured in Figure 5.

Model	Accuracy	F1	MSE
First	0.72	0.63	0.15
Second	0.64	0.61	0.18

Figure 5: Evaluation of the first two variants of the model

For the last two modelling perspectives, the performance of the model shows that the fourth variant makes more correct predictions than the second model (i.e., accuracy), performs overall better in terms of precision and recall (i.e., F1 score), and has smaller prediction errors on average (i.e., MSE). The corresponding evaluation metrics and values are captured in Figure 6.

Model	Accuracy	F1	MSE
Third	0.61	0.59	0.20
Fourth	0.68	0.67	0.16

Figure 6: Evaluation of the last two variants of the model

The results obtained point out the fact that the first and the fourth variants of the model perform better than the second and third variants. This represents a valuable finding and show that such a complex process like the proportionality assessment in military operations can be understood and modelled better either from a more

simplistic angle as expressed by the first model variant, or from a more advanced angle as expressed by the fourth model variant.

5. Conclusions

During the history of human civilisation, various conflicts and wars were carried out due to different reasons and objectives. These events represent important lessons to be learned and reflect the capacity to innovate and be resilient while considering relevant legal, ethical, and social implications and consequences that they imply. Directly related to these are the effects, and in particular, the harm and damage experienced by civilians and civilian infrastructure, respectively. These represent entities that need to be protected in time of war. A critical component in the planning and execution of military operations is the proportionality assessment which calls for a balance between the anticipated military advantage against the expected collateral damage on civilians and civilian objects. This implies aiming at minimizing civilian casualties while allowing legitimate military actions and ensuring that foreseeable collateral damage is not excessive in relation to the concrete and direct military advantage.

In the last decade, recent advancements in the AI domain sparked interest in its potential applications for decision-making support systems as well as for dynamic analysis and assessment in various military activities and processes. This represents a recent research area in relation to conducting the proportionality assessment in military operations and aspects such as the importance of contextual information, subjectivity, and uncertainty surrounding this process need to be accounted. In this realm, this research proposes a novel hybrid AI model based on the Neuro-Fuzzy technique and considers four development perspectives for execution. The flexibility and adaptability of Neuro-Fuzzy systems make them particularly valuable in cases and for problems where traditional methods struggle to capture the full complexity of the problem. Based on the evaluation conducted, the results show that two out of the four variants considered show potential for further application. From here, further research perspectives can be identified to include other AI techniques in the development phase as well and to build an advanced modelling and simulation environment such as a digital twin (Maathuis, 2022) and a corresponding user interface in a responsible and trustworthy manner.

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