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Research paper

Artificial intelligence-driven protocol for secure and standardized maneuver control in electrical substations

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ABSTRACT

Notwithstanding recent advances in substation automation, no existing protocol integrates human–machine interaction, intelligent interlocking, operational autonomy, and artificial intelligence analysis in sequential maneuvering contexts. This study proposes an automated interface to optimize and control switching operations in electrical substations by integrating operational protocols, automated documentation generation, and artificial intelligence techniques with interactive graphical visualization. The developed solution enables sequential command execution, classification of operational events, and automatic generation of auditable reports, enhancing accuracy and traceability in operations. A total of 108 real files, corresponding to 54 events with documented failures, were analyzed and used to train and validate a recurrent convolutional neural network model. The system achieved an accuracy of 82.92% in error detection, along with reductions of 42.7% in the average operational response time and 38.5% in failure frequency. In addition to standardizing procedures, the interface demonstrated adaptability to different substation topologies and configurations, establishing itself as a scalable, secure, and efficient alternative for assisted operation environments. The results suggest that the proposed solution contributes to reducing inconsistencies, increasing decision-making autonomy, and strengthening operational safety in the power sector.

1. Introduction

The Power System (PS) is responsible for the distribution of electricity from generation to final distribution. The continuous increase in energy demand, driven by economic growth, has increased the complexity of this system, requiring more refined control strategies and the adoption of innovative technologies (Azar, 2019). In this context, major operation centers oversee large regions, ensuring continuity and security in the power supply. Substations, in turn, serve as strategic points for interconnection, control, and protection of transmission and distribution networks (Souza Junior and Freitas, 2022; Bakkar et al., 2021). Their quantity and location are determined based on topography, population density, and energy demand to optimize power flow and ensure stability of supply (Stern, 2019; Ten and Hou, 2024). Alternating current (AC) transmission, widely used due to its ease of voltage transformation, improves the flexibility and operational efficiency of the PS (Ibrahim et al., 2020). In this scenario, the integration of new technologies and effective coordination between transmission agents are required to maintain the security and reliability of the system (Ten and Hou, 2024).

In substations, the interaction between transmission agents, who frequently share transformers and other equipment, presents significant

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[1] An international standard defining communication protocols and data models for substation automation and protection.
[2] American National Standards Institute.
[3] Conseil International des Grands Réseaux Électriques.

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challenges, particularly in terms of effective communication and cooperation (Hunt et al., 2019; Chen et al., 2023). To mitigate these challenges, standards such as IEC61850[1] and IEEE regulations establish protocols that enable the integration of devices from different manufacturers (Filipovic-Grcic et al., 2023; International Electrotechnical Commission, 2020), promoting coordinated and secure operation (IEEE Power and Energy Society, 2022; International Electrotechnical Commission, 2022; Aftab et al., 2018). In addition, guidelines from organizations such as ANSI[2] and CIGRE[3] define requirements for protection and continuity in the power supply (Esmail et al., 2019; International Electrotechnical Commission, 2021). The adoption of these standards facilitates the implementation of interoperable automation systems, which control circuit breakers, disconnect switches, and transformers automatically (Abood and Fuller, 2023; Maleki et al., 2025; Dabush et al., 2023). However, despite automation and standardization, the complexity of operations still requires human intervention, which requires intuitive interfaces and continuous training to minimize errors and improve operational safety (Kumar et al., 2023; Six et al., 2021).

Recent advances in sequential maneuver automation in substations have prioritized operational safety and process efficiency. Sequential control systems enable the simultaneous management of multiple subsystems with a single command, enhancing integration and reducing the need for manual intervention (Ge et al., 2019). The digital transformation of substations has facilitated the integration of renewable energy sources and driven the modernization of power grids (Kanabar et al., 2022; Rajaoarisoa et al., 2025). Emerging technologies, such as smart sensors, reduce maintenance costs and simplify system design (Twomey, 2018), while automated control systems incorporate validation functions to ensure the correct execution of protocols (Nie et al., 2020; Tan et al., 2020). These innovations contribute to safer and more coordinated operations (Liang and Xie, 2022; Gerasimov et al., 2019).

Despite these advances, human errors still affect the reliability of the power system, particularly during maneuver execution and the issuance of work permits (Dabush et al., 2023). The number of maneuvers performed, the operator's experience, and the duration of training directly influence the error rates (Liang and Xie, 2022; Shiqi et al., 2022). Strategies such as the use of simulators and periodic training are necessary to reduce operational failures (Krastev and Georgiev, 2020; Dai et al., 2021), as well as to improve operational quality and maintenance (Gerasimov et al., 2019; Rajaoarisoa et al., 2025). Poorly designed interfaces and system design flaws also compromise task execution and increase the likelihood of failure (Liu et al., 2021; Oikonomou et al., 2021). Thus, the combination of proper training, simulators, and optimized interfaces can contribute significantly to reducing human errors and improving operational safety (Lavrov et al., 2019; Oudina et al., 2023).

Among the various operational risks in power system environments, coordination failures during load switching under fluctuating network conditions represent a particularly critical manifestation of human error (Younesi et al., 2022). Inconsistent interlocking procedures, delayed communication, or misinterpretation of commands can trigger unintended feeder activation, leading to overcurrent conditions or involuntary load shedding (Rajkumar et al., 2023; Anderson et al., 2023). These risks are exacerbated under pressure and limited situational awareness (Pooladvand and Hasanzadeh, 2023). To address such challenges, intelligent supervisory systems capable of real-time validation, predictive control (Calixto et al., 2025), and adaptive coordination have been proposed to improve operational consistency and substation resilience (Mohammadi et al., 2022; Girdhar et al., 2024; Liberati et al., 2021).

Traditional tools used in control centers, such as Excel spreadsheets and manual switch plans, impose severe limitations on the responsiveness and consistency required by modern power grids. These approaches lack interoperability, depend on static configurations, and require multiple manual steps, often involving handwritten procedures comprising over 100 actions (Ockwell, 2014). Such constraints hinder the adaptation to dynamic network topologies and increase the likelihood of operational errors under high-pressure conditions. As grid complexity increases, there is a growing demand for intelligent systems capable of supporting automated decision making, reducing plan validation delays, and ensuring seamless integration between planning and execution environments.

Current substation automation systems still exhibit significant operational limitations, particularly in layers such as real-time interlock validation, load transfer coordination, and issuance of work permits. These processes largely depend on manual protocols or fixed rule systems, offering limited adaptability to dynamic topologies (Sarry et al., 2018; Madurasinghe and Venayagamoorthy, 2022). In critical contexts such as post-fault restoration and complex maneuver sequences, these limitations compromise operational consistency and safety, while also restricting decision making by human operators (Zongzheng and Yanze, 2022). The lack of continuous validation modules capable of interpreting operational sequences under changing electrical and organizational conditions reduces the responsiveness and adaptability of the system. Although recent studies propose distributed multi-agent architectures to enhance semantic interoperability and coordination (Santos et al., 2019; Mihai et al., 2024), this work introduces an alternative centralized framework that integrates sequential modeling and contextual analysis. The proposed approach aims to address these gaps through an intelligent interface that does not require agent-based infrastructure, but still enables scalable and autonomous substation operation (Listopad, 2020).

In parallel with architectural advances, artificial intelligence (AI) has emerged as a promising solution to enhance error detection and operational efficiency in transmission substations. Recent advances in machine learning, particularly deep learning, have significantly impacted event classification and process automation (Wang et al., 2023b; Zhang et al., 2024; Ahmadi et al., 2022). Convolutional neural network (CNN) models have achieved high precision in detecting disturbances in power quality (Edward et al., 2024). Temporal data analysis of phasor measurement units (PMU) enables more precise assessment of substation operating conditions (Niazazari et al., 2021; Pavlovski et al., 2021; Ahmadi et al., 2022). Furthermore, the combination of convolutional and recurrent neural networks (RCNN) has proven effective in integrating spatial and temporal features (Hendi et al., 2023; Hassan and Mahmood, 2018; Wang et al., 2023b), while architectures such as Gated Recurrent Unit (GRU) and bidirectional neural networks improve pattern detection and operational predictability (Orr et al., 2018; Nguyen et al., 2019; Gao et al., 2021).

Sequential event analysis is necessary to identify operational patterns, anticipate failures, and adjust control strategies. Unsupervised methods, such as `event2vec`, are employed to model temporal relationships in operational records, extracting relevant features for error classification (Ahmed et al., 2023; Zhang et al., 2024). Heuristic strategies, combined with temporal normalization and event segmentation, refine the construction of representative data sets for the training of predictive models (Magallanes et al., 2019). Furthermore, advanced optimizers, such as the Tree-Structured Parzen Estimator (TPE), enable efficient neural network hyperparameter tuning, ensuring a better balance between precision and convergence speed (Watanabe and Hutter, 2022, 2023).

In the context of maneuver sequencing in transmission and generation substations, no existing protocol integrates human-machine interaction, enables interlocking between equipment, ensures autonomy in system maintenance and evolution, and incorporates AI (Liang and Xie, 2022). This gap affects operational safety, as the lack of standardization can lead to inconsistencies in maneuver execution and failures that compromise the functionality of the power system. Therefore, enhancing automation and interoperability is required to address the increasing complexity of the Power System and the growing demand for greater reliability (Kumar et al., 2023).

In this context, this study proposes the development of an automated interface for optimizing and controlling maneuvers in electrical substations, utilizing AI for operational error detection, operation standardization, and automated procedure documentation. The model integrates RCNN to analyze recorded events, considering both textual features and temporal dependencies (Bakkar et al., 2021; Ebrahimi and Rastegar, 2024). In addition, it aims to establish procedures that ensure result consistency and enable system autonomy across different operational areas (Ten and Hou, 2024). The integration of these technologies improves maneuver reliability by reducing operational inconsistencies, optimizing the system response, and promoting process standardization and integration (Oudina et al., 2023). Consequently, this approach is expected to minimize human errors, improve coordination among agents, and improve the safety and efficiency of power system operations.

The hypothesis of this study is that the development of an AI-based automated interface for operational error detection, documentation optimization, and intelligent interlocking between maneuvering equipment can improve operational efficiency and autonomy in substation control, even as the complexity of the power system increases (Ge et al., 2019). The proposed interface should integrate advanced control, monitoring, and machine learning functions, reducing inconsistencies and improving real-time decision-making (Tan et al., 2020; Oikonomou et al., 2021), while also minimizing the need for manual interventions and the occurrence of human errors (Krastev and Georgiev, 2020; Ebrahimi and Rastegar, 2024).

The overarching objective of this study is to develop an automated interface with AI analysis to enhance human-machine interaction, enable intelligent interlocking between maneuvering equipment, and ensure greater autonomy in system operation and evolution. To achieve this objective, the following specific goals are established: i) implement an automated documentation protocol using machine learning to enable user-independent document generation, reducing inconsistencies and improving operational traceability, ii) develop a neural network-based procedure to ensure the consistency of the results under various operational conditions, using deep learning models to analyze maneuver patterns and provide real-time recommendations, iii) adopt intelligent automated documentation generation among transmission agents by integrating sequential event analysis and predictive algorithms to reduce operational errors and streamline information exchange, iv) enable autonomous system use across operational areas by employing an AI-optimized interface for document generation on demand based on maneuver requirements, promoting efficient coordination between different agents and improving operational safety.

Regarding feasibility, the project focuses on the costs associated with software, hardware, and development, without requiring significant investments in materials or physical equipment, making its implementation accessible to energy companies and other industries that require automation and process control (Gaspar et al., 2023). The applicability of this study extends beyond electrical substations, as it can be utilized in various industrial sectors to improve operational efficiency through automated systems, machine learning, and intelligent documentation. Similar RL-based frameworks, such as the sim-to-real architecture proposed for energy management in fuel cell electric vehicles (Lei et al., 2025a), and physics-informed data-driven paradigms for hybrid powertrain optimization (Lei et al., 2024), demonstrate how domain knowledge can be effectively integrated into AI-driven solutions, enhancing generalization capabilities and facilitating operational transferability in complex environments.

The article is structured as: Section 2 presents the theoretical foundation, providing the necessary background to understand the adopted methodology and the expected results. Section 3 details the development of the study, describing the methodological workflow and implementation of the proposed protocol, from the design of the automated interface to the results obtained using AI. Section 4 discusses the findings, analyzing the impact of the methodology on maneuver optimization and the reduction of operational errors. Finally, Section 6 presents the conclusions, consolidating the study's contributions to the automation and safety of the power system.

2. Theoretical background

This section presents the basic concepts related to maneuver sequencing in transmission and generation substations, with an emphasis on transformations driven by automation and digitalization of operational processes. It begins with a discussion of the evolution of approaches used to structure maneuver procedures, including the technologies adopted, the control models implemented, and the challenges associated with standardizing operations. Subsequently, it examines the limitations of traditional methods and the prospects of substation automation, highlighting the integration of emerging technologies such as digital twins, edge computing, and interoperable communication protocols. Finally, it addresses the contributions of machine learning to event classification, including neural network architectures, as well as recent optimization strategies and temporal analysis techniques applied in the power sector.

2.1. Automation and foundations of maneuver sequencing

Maneuver sequencing in transmission and generation substations refers to the systematic organization of operations aimed at circuit reconfiguration, equipment maintenance, and fault response, with an emphasis on operational safety and system stability (Sun et al., 2021; Mondragón Bernal et al., 2022). Conventional approaches, such as control spreadsheets and manual records, have limitations due to their susceptibility to human error and operational inconsistencies (López et al., 2020; Vai et al., 2021). In this context, optimization models such as mixed-integer linear programming and mixed-integer second-order cone programming have been used to reduce costs and restoration time, although their integration with automated documentation processes remains a relevant technical challenge (López et al., 2020; Vai et al., 2021; Biswas and Centeno, 2022).

In addition to optimization strategies, the automation of modern substations is structured around mesh topologies that ensure the redundancy required for continuous power supply (Xu et al., 2024; Rubinstein and da Vinha, 2018). Digital technologies and intelligent devices are used for continuous monitoring and fault diagnosis, supporting predictive and corrective maintenance strategies (Bouffard-Vercelli and André, 2021). Distributed architectures integrated with protocols such as the Modular Digital Bus (MODBUS) and Ethernet networks enable remote supervision and connectivity with Supervisory Control and Data Acquisition (SCADA) systems, enhancing operational control and management capabilities (Chaves et al., 2022).

Automated generation of maneuver sequences has been investigated through expert systems and Petri nets, which contributes to compliance with safety regulations and to the reduction of response time in critical situations (Kong et al., 2025; Six et al., 2021; Kottmann et al., 2023). Furthermore, process simulations and cognitive platforms have been applied to the planning of operations in substations and power plants, promoting greater consistency and safety in operational decision making (Dandea and Grigoras, 2023). In this context, automated documentation and the modeling of interconnected topologies are relevant for coordination between power sector agents, supporting risk mitigation and standardization of operational practices (Kumar et al., 2024; Almeida et al., 2022; Pirouzi et al., 2022).

Emerging technologies such as augmented and virtual reality offer significant potential to enhance operator training and the understanding of interlocking protocols (Nie et al., 2020; Cyrino et al., 2023; Bouffard-Vercelli and André, 2021). When integrated into digital environments, these solutions contribute to the development of more flexible and adaptive operational systems, allowing real-time monitoring capabilities (Hernandez et al., 2017; Kelm et al., 2022). Although advances in sequential control and integrated automation have improved operational precision (Hengxuan et al., 2019), the consolidation of a fully integrated process that connects automated documentation with the execution of standardized maneuvers still requires further research and development efforts (Morais et al., 2024).

2.2. Current challenges and future perspectives in substation automation

Despite advances in automation and digital integration, the scheduling and execution of maneuvers in transmission substations still often rely on the manual completion of digital forms by pre-operation personnel, followed by review and submission to the team responsible for real-time execution (Kulkarni et al., 2021). Although some utilities employ expert systems based on historical maneuver data to accelerate adaptations, these solutions remain limited to partial automation (Oikonomou et al., 2021). Graph theory-based models or bond graph structures have been applied to automatically generate maneuver sequences, but they frequently overlook critical aspects of coordination with the TSO (TSO)[4] and other transmission agents (Alvarez-Alvarado et al., 2022).

To address these limitations, tools have been developed to automate the completion of work orders and operational forms, with the potential to reduce maintenance team preparation time by up to 2.2 h per day (Vladimirovich Borodin et al., 2020). However, complete integration of these solutions into operational workflows still requires structural adaptations to ensure system continuity and interoperability across different operational environments.

In parallel, substation automation has advanced toward the full digitalization of processes through the incorporation of technologies such as AI, machine learning, and smart sensors (Santos et al., 2024; Torres et al., 2023). These technologies enable the identification of anomalies and the execution of real-time adjustments, thus improving infrastructure resilience. The transition to digital substations requires the replacement of legacy protocols with standards such as IEC61850, which improve efficiency and interoperability between devices from different manufacturers (Hasan et al., 2023; Aftab et al., 2020). This transformation also facilitates remote maintenance and optimizes data analysis, supporting intelligent asset management (Kanabar et al., 2022).

Digitalization also facilitates the integration of distributed energy resources and the adaptation of power grids to the growing share of renewable energy sources (Kapil and Prasad, 2022). Technologies such as digital twins, cloud computing, and edge computing have enabled remote monitoring and predictive maintenance, positioning substations as autonomous energy management centers (Huang et al., 2017; Shiqi et al., 2022). In such environments, diagnostic, protection, and control capabilities are significantly expanded, directly impacting reliability and operational efficiency.

Cybersecurity represents a strategic pillar in substation automation, particularly in light of the increasing network connectivity and system complexity. Protection against digital threats must be embedded from the design phase, through redundant communication architectures and advanced security protocols (Horalek and Sobeslav, 2023). This integration strengthens system protection and enhances adaptability to evolving generation and consumption profiles (Nirmal, 2020).

The digital transformation of substations marks a milestone in the evolution of the power sector, with positive impacts on operational efficiency, cost reduction, and energy supply security (Azar, 2019). The continued advancement of digital and communication technologies is expected to enable more efficient coordination among agents and more precise control of operations, positioning substations as strategic components in the modernization of the energy sector (Fan and Li, 2023; Hunt et al., 2019).

2.3. Machine learning techniques for event classification

The application of deep learning techniques has progressed significantly in the classification of events in power transmission substations. The CNN has been used to improve data preprocessing and improve accuracy in disturbance detection (Edward et al., 2024). Validation of these classifiers using real-world data reinforces the importance of temporal records obtained from PMU (Niazazari et al., 2021; Pavlovski et al., 2021). Reliability-enhancing strategies include the analysis of specific signal patterns and the reduction of classification errors through adaptive adjustments (Jie et al., 2020). Complementary approaches, such as the use of critical slowing indicators and image-based classification methods, have achieved accuracy levels exceeding 98% (Austin et al., 2021; Balouji and Salor, 2017). Adaptive neural networks also show potential for fault identification and decision automation, contributing to the resilience of power systems (Malik and Rajneesh, 2017; Thomas and Shihabudheen, 2023).

Furthermore, temporal analysis techniques have been extensively developed in other fields, such as healthcare and logistics, and show potential for application in the context of transmission substations. These approaches enable the identification of patterns and trends in event sequences, facilitating the prediction of future occurrences and the detection of meaningful relationships between variables in multivariate environments, such as electronic health records (Rodrigues and Zárate, 2024; Wang et al., 2023a). Unsupervised methods, such as `event2vec`, have been used to model latent relationships between events (Ahmed et al., 2023). Heuristic strategies based on the analysis of textual descriptions and short intervals between events also demonstrate the potential to enrich datasets and improve the representativeness of failure-related classes.

The integration of CNNs with sequential models, such as GRU, has enhanced event identification by combining temporal dependencies with structural attributes (Hendi et al., 2023; Hassan and Mahmood, 2018; Orr et al., 2018). Recent advances include the incorporation of graph convolutional networks into recurrent architectures, the expansion of the use of dynamic structures for predictive monitoring and the classification of temporal relationships (Rama-Maneiro et al., 2024; Dai et al., 2019). Strategies that combine multiple vector representations with temporal feature extraction techniques have also been explored to strengthen the modeling of complex event sequences (Nguyen et al., 2019; Kong and Yang, 2024).

In the field of optimization, various approaches have been investigated to improve algorithmic performance through the selection of hyperparameters. The TPE method has stood out for its efficiency in constrained scenarios, outperforming traditional methods in terms of accuracy and generalizability (Rajalakshmi and Sulochana, 2023; Watanabe and Hutter, 2023). Recent strategies have incorporated uncertainty modeling into the search process, allowing greater adaptability to data variability and operational constraints (Békési et al., 2024). These advances reinforce the applicability of deep learning models to critical classification tasks in the power sector.

3. Methodology

This section presents the methodology developed for implementing the user interface designed to enhance human-machine interaction, enabling integrated control of interlocks between maneuvering equipment, such as circuit breakers and disconnect switches in substations, and optimizing the error detection process using AI. Fig. 1 illustrates the entire methodological workflow, covering the definition of rules through the execution and monitoring of maneuvers.

The proposed approach automates maneuver sequencing, eliminating the need for manual data entry or searching corporate databases during operational planning. The system utilizes automatically generated data to manage maneuvers based on predefined rules, facilitate communication among agents, and track all executed actions. The methodology incorporates mechanisms to record and monitor interactions between operators and agents, ensuring consistency and traceability of executed activities.

[4] Entity responsible for the operation, maintenance, and development of the power transmission network, ensuring real-time system coordination and equitable network access for all users (Uzum et al., 2024).

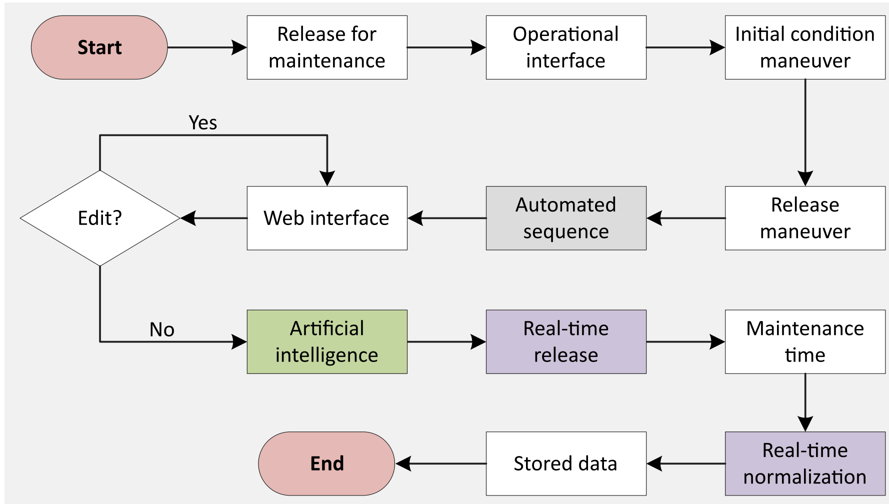


Fig. 1. Flowchart of the proposed methodology.

3.1. Release protocol

The methodological workflow illustrated in Fig. 1 begins with a release request for transmission line maintenance, followed by the operator's access to the operational interface to control and monitor switching operation. Then, the initial condition maneuvers are executed, where the operator replicates the real-time conditions of the system before performing the release maneuvers. If a circuit breaker is already open, this condition must be reflected in the initial settings before setting up, as illustrated in Fig. 2. Through automatic sequencing, the system generates a document containing the release and normalization sequence, together with the necessary information for communication with other agents.

As shown in Fig. 2, the system utilizes multiple databases to manage information in an organized manner: i) BD_1 stores system equipment data, including their states (e.g., open or closed), ii) BD_2 records the initial maneuver scenario and interface maneuvers (simulation) to visualize equipment conditions before operations, iii) BD_3 logs executed maneuvers and serves as a reference for the normalization process, iv) BD_4 registers maneuvers and interactions with the TSO and other agents, being processed by the Web interface for display and auditing, and (v) BD_5 stores all release and normalization data, serving as the final reference for auditing and formal report generation.

The maneuver sequencing process follows a chronological flow, beginning with the selection of the maneuver equipment (SME), i.e., the equipment to be disconnected, isolated, or grounded, as required. This process involves communication between the maneuver executor and the TSO, who is responsible for authorizing the de-energization of the equipment. Once authorization is obtained, the executor contacts other transmission agents (DCoA) if circuit breakers belonging to these agents need to be maneuvered. Subsequently, the necessary documentation is issued, such as the Impediment Authorization (IA) or Operational Message (OM), depending on the type of operation.

With the necessary authorizations in place, circuit breaker maneuvers (DMD) are executed to safely disconnect the equipment. Subsequently, disconnect switch maneuvers (DMCS) are performed, including switch opening, grounding switch closure, and the application of security locks (DBCS) to ensure proper isolation. Disconnect switches can be in one of three states: open (CSA), closed (CF), or locked (BdC), indicating that the switch is in secure condition with the insertion of a safety tag.

In certain situations, the system verifies whether maneuvers have been blocked (MB) or released (ML) based on predefined interlocking logic conditions to ensure system safety. If necessary, the span completion maneuver (DSOC) is executed upon obtaining new authorization from the TSO to ensure substation reliability before reintegrating the equipment into the National Interconnected System (NIS).

If the involvement of other agents is required for span completion (DCVoA), maneuvers are executed after confirmation from the relevant agents. Circuit Breaker Closure Maneuvers for span completion (DMCV) finalize the process, ensuring coordination among teams. During span completion, the system verifies the equipment isolation conditions (IoA) and removal of isolation by another agent (RIoA) to ensure that all equipment is safely reintegrated.

In the operational interface, the equipment is graphically represented, allowing users to execute commands and modify their states. Substation (SE) information, including location, equipment, voltage values, and state, is stored in the database BD_2. Before each maneuver, an interlocking routine verifies the feasibility of operations based on predefined logical diagrams. The system displays the general single-line maneuver diagram, replicating the supervisory system used in operations. Executed actions are shown in the event list, chronologically organized within the circuit breaker maneuver display (DMD) or the disconnect switch maneuver display (DMCS), enabling real-time tracking of maneuver execution times.

The system automatically generates and issues documents to other agents based on the processed data. Formal reports are used for the coordination and release of equipment between companies. Before maneuver execution, text inputs are entered into the system interface along with input data, according to the type of document to be issued: Impediment Authorization (IA) or Operational Message (OM). The IA is issued when the system verifies that the circuit breaker of the other agent is isolated. For OM issuance, the system checks whether the circuit breaker of the other agent will be maneuvered. If this condition is met, the document is generated with the necessary information, including the circuit breaker name and the impediment condition to be applied.

At the end of the process, the system exports the data stored in the database BD_5, ensuring consistency and traceability for auditing and the generation of formal reports. Once all maneuvers are completed, the equipment is made available to the TSO through the make available to the TSO display (DDO), signaling the completion of the process.

3.2. Interlocking protocol and equipment state definition

The interlocking protocol utilizes the database BD_1, which is processed with each command executed during the normalization process. The database BD_6 stores the maneuver sequence in reverse order, corresponding to the inverse execution of the release process. The

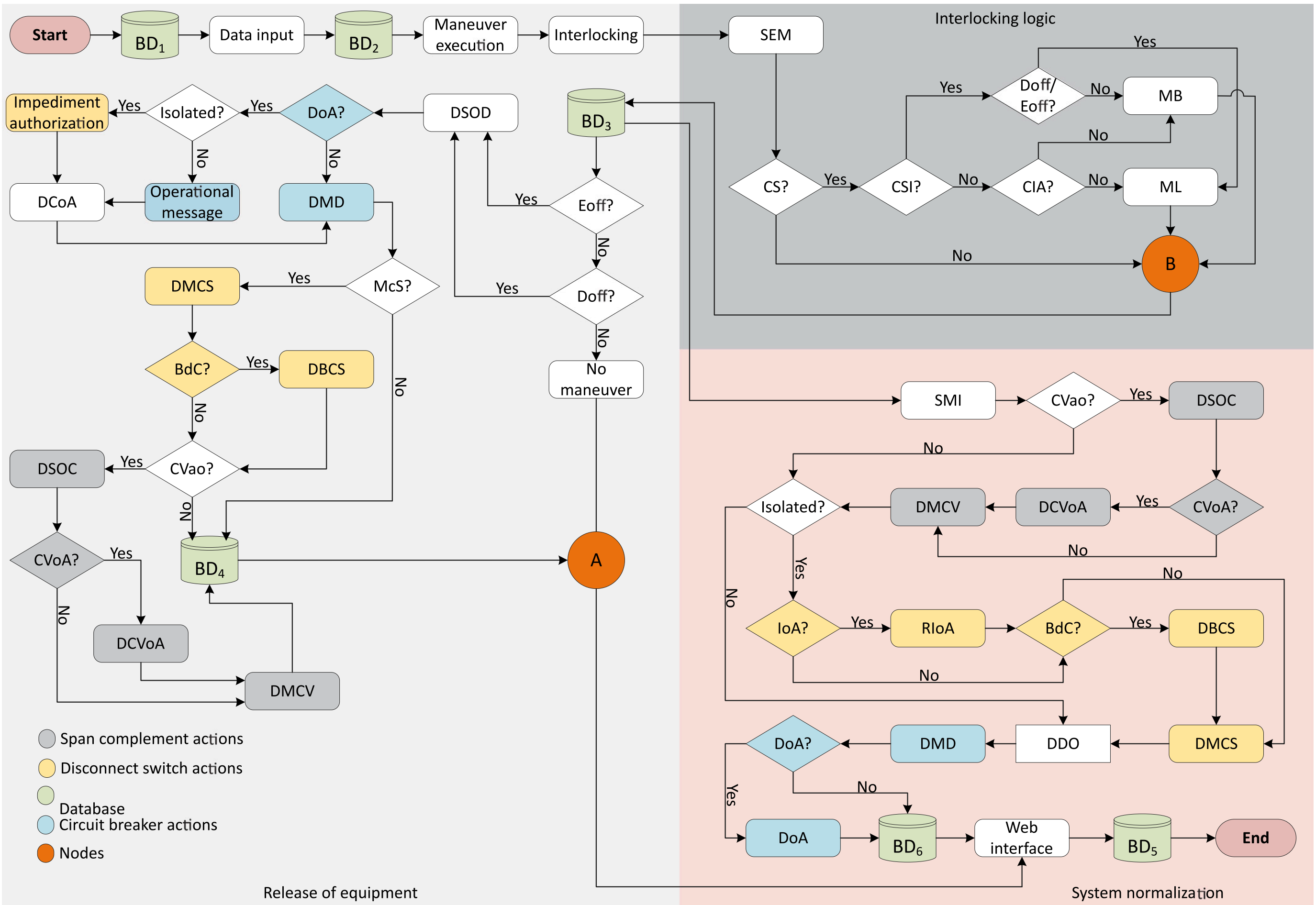


Fig. 2. Flowchart of the release protocol.

interlocking flow, illustrated in Fig. 2, resumes after node **A**, beginning with the selection of the switching equipment (SME), which defines the specific device to be operated. After selection, the system verifies whether the equipment corresponds to a disconnect switch (CS). If so, it proceeds to identify the switch type, specifically whether it is an isolating disconnect switch (CSI). If the equipment is a CSI, the system checks whether the device isolated by the switch is an open circuit breaker (Doff) or deenergized equipment (Eoff) and whether it is in the off state (Doff or Eoff). If the equipment is deenergized, the maneuver is classified as released (ML), otherwise, it is blocked (MB). If the disconnect switch is not of type CSI, the system verifies whether it is in the open isolating switch state (CIA). If the switch is open, it is classified as ML, otherwise, it is MB.

The system classifies the states of the circuit breakers and disconnect switches to ensure proper interlock control. A circuit breaker is classified as isolated when both associated isolating disconnect switches (CSI) are open. This verification is performed by counting the associated switches and checking their positions. A circuit breaker is in the open state when its position indicates open and in the closed state when its position indicates closed. To achieve this, the system identifies the location of the associated switches within the circuit breaker's address. Disconnect switches (CS) have three possible states and are considered locked (BdC) when a safety tag is inserted into the control panel. In this case, the locked condition is indicated by the red tag in the description in the address associated with the disconnect switch state.

For general equipment, the system uses two variables to define the state of the transmission function: a list grouping all equipment according to its function, such as the transmission line, bus bar or reactor, and a sublist indicating which circuit breakers belong to each function. The transmission function state is determined by the circuit breakers and disconnect switches states. The function is classified as energized when at least one circuit breaker at each terminal is closed, deenergized when all circuit breakers are open, isolated when the isolation switches are open or at least one disconnect switch connected to this function is open, and grounded when the grounding switch is closed.

When the span completion (CVao) is achieved, the isolating disconnect switch of the transmission function remains open, and the span circuit breaker is closed. To ensure that the system correctly identifies the state of the equipment, a function was developed to verify the logical state and associate this information with the system scenario in the database BD_3. Based on this verification, it is possible to determine whether the equipment is in a deenergized, isolated, or grounded state, ensuring that the maneuver commands are executed safely. After verification and maneuver execution, the system finalizes the process and stores all information in the database BD_5.

For equipment belonging to other agents, the need for additional span completion maneuvers executed by third parties (CVoA) or negotiations with the TSO is assessed, generating the corresponding authorizations: i) TSO request display for span completion (DSOC), ii) other agents' span completion display (DCVoA), and (iii) span completion maneuver display (DMCV). After all maneuvers are completed, the system returns to its initial state and verifies whether all operations were successfully executed, ensuring data integrity and consistency across the utilized databases.

3.3. Normalization protocol

The normalization protocol begins with the use of the latest generated file in the database BD_3, which contains the maneuvers executed during the release process. From this file, the system generates the Inverted Maneuver Sequence (IMS), where maneuvers are organized in reverse order relative to the release process. Based on this structure, the system verifies the need for span decompletion, evaluating whether the span has been completed (CVao), as illustrated in Fig. 2, continues after node **B**. If decompletion is required, the request is forwarded to the TSO via DSOC. Upon TSO authorization, the presence of circuit breakers from other agents involved in CVoA is verified. If confirmed, the maneuver for opening these circuit breakers is recorded in DCVoA and, subsequently, their opening is registered in DMCV.

After opening the span, the system verifies that the equipment, including circuit breakers and associated devices, has been properly isolated. If isolation is confirmed, the system checks the isolation of equipment belonging to other agents (IoA). If confirmed, a request is issued for the removal of this isolation via the Removal of Isolation by another agent (RIoA) display. At this stage, all necessary maneuvers for the removal of isolation, including closing the isolation disconnect switches, are executed. If the equipment from other agents is not isolated, the system checks for the presence of blocked disconnect switches (BdC). In case of blockage, a request for its removal is issued through the Disconnect Switch Blocking display (DBCS). Once removal is confirmed, the disconnect switch maneuvers required for isolation removal are recorded in DMCS. If isolation removal or unlocking is not necessary, the equipment is made available to the TSO via the Make Available to TSO display (DDO).

The circuit breaker maneuvers are then verified through the Circuit Breaker Maneuver Display (DMD). If circuit breakers from other agents (DoA) are involved, a request for their closure is issued, with the respective maneuvers recorded in the database BD_6. Once the normalization maneuver sequence is generated, all data are imported into the Web interface, allowing the executor to edit and input the maneuver names and execution times. Subsequently, a report is generated and recorded in the database BD_5, which stores both the release and normalization maneuver sequences. During the normalization process, issuing new documents to other agents is not required, as all necessary negotiations were completed during the release process.

3.4. Data representation, preprocessing, and motivation for intelligent classification

The dataset consists of structured records of operational events, comprising textual descriptions and numerical variables stamped with time. Numerical features are normalized, textual descriptions are tokenized, and events are organized sequentially. Redundant entries are removed to preserve causal patterns associated with system failures. Data are divided into training, validation, and test sets using stratified sampling to maintain class proportions. Due to the imbalance between normal events and those related to failures or incorrect maneuvers, synthetic oversampling (SMOTE) (Mukherjee et al., 2021a) is applied, along with class weighting during model optimization. This strategy aims to improve the representation of minority classes and reduce bias in the training process (Mukherjee et al., 2021b; Farzad, 2020).

The methodology for operational error classification is structured into three main stages: (i) data preparation, (ii) construction of the machine learning model, and (iii) hyperparameter optimization. The objective is to develop a classifier capable of distinguishing between correct and incorrect events using an RCNN, which enables the joint analysis of textual descriptions and temporal patterns. In addition, two auxiliary resources support the classification process: (i) an error dictionary containing detailed descriptions of documented failures and (ii) a structured error library used for the identification and categorization of anomalies.

To preserve contextual and temporal dependencies between events, the dataset is segmented into sliding windows composed of consecutive records. The choice of window size plays a critical role in model resilience: short windows may not capture sufficient information for reliable classification, while longer windows offer a broader historical perspective, improving the model's tolerance to noise, missing values, and isolated anomalies. This segmentation facilitates the detection of sequential patterns and improves the representativeness of the training data.

Preliminary error detection is performed using heuristic rules derived from documented patterns. These rules assess the presence of keywords in textual descriptions and inconsistencies in time intervals between adjacent events. Sequences exhibiting frequent transitions, missing descriptions, or unusually short time gaps are flagged as potential errors. This rule-based enrichment process enhances the generalizability of the model by incorporating domain knowledge into the training stage. During inference, similar heuristic routines are used to generate interpretative alerts when input sequences deviate from expected patterns, thereby signaling a potential reduction in prediction reliability.

The model architecture is designed to address the limitations observed in current substation automation systems, such as the lack of real-time interlocking validation and limited support for work permit issuance in dynamic topologies. The proposed approach overcomes these constraints through sequential event modeling and the integration of contextual attributes into operational record analysis. Although experimental validation focuses on specific substations, the solution is designed to be generalized to voltage levels and grid configurations. It does not rely on the physical topology of substations, but rather on the semantic and sequential structure of recorded events. In more complex scenarios or distribution networks, additional contextual attributes can be incorporated as numerical variables without requiring structural modifications to the model. This flexibility supports the scalability of the approach in different operational contexts, including those with a high penetration of renewable energy sources or evolving topologies (Fulda et al., 2024; Subramanian et al., 2021).

3.5. Architecture and optimization of a deep learning model for event classification

The architecture adopted in this study is a RCNN, selected for its ability to simultaneously capture spatial and temporal dependencies, an essential requirement for analyzing sequences of operational events in electrical substations. The convolutional layers extract hierarchical patterns from structured textual descriptions, while the recurrent components model the temporal progression of these events, capturing sequential dynamics relevant to error identification (Hendi et al., 2023; Alom et al., 2021). Compared to standalone convolutional models, which lack temporal context, or recurrent models such as long short-term memory (LSTM) and GRU, which do not inherently capture spatial hierarchies, RCNN provides a unified framework that enables end-to-end learning from both content and chronology (Xu et al., 2019). This architectural integration addresses limitations found in conventional models, which often fail to represent dependencies between temporally distributed events and spatially related equipment, particularly in dynamic substation topologies (Dwivedi and Tajer, 2023).

The model is preceded by an input preprocessing pipeline, which tokenizes and vectorizes structured textual descriptions, while numerical variables, such as historical error labels, are normalized and encoded. These steps ensure consistency and compatibility between data types before entering the RCNN core. The tokenized text is then transformed into dense vector representations by the embedding layer and processed by CNN to extract local patterns. In parallel, normalized numerical variables are processed through dense layers to identify correlations between temporal attributes and error occurrences. The architecture combines embedding, convolution, and pooling techniques to ensure

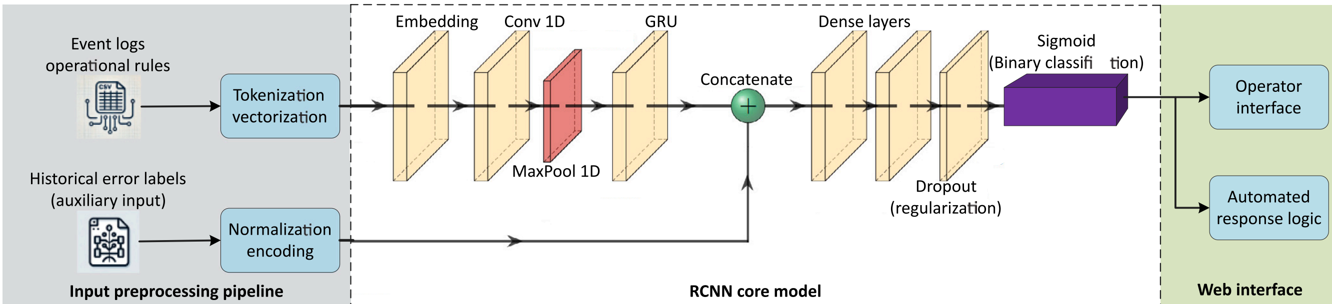


Fig. 3. Model architecture for event classification.

efficient data representation. A pooling mechanism reduces the dimensionality of feature maps, while preserving relevant classification information and optimizing model performance.

Sequential event modeling is performed using RNNs, allowing the capture of temporal patterns within event sequences. The output of the convolutional layers is processed by a GRU, which models dependencies by considering the influence of preceding and subsequent events on the classification outcome. GRU was selected because of its favorable performance in small data sets compared to LSTM networks, which offers effective long-term dependency modeling with lower computational complexity. To integrate both textual and numerical information, the recurrent output is concatenated with a parallel input consisting of pre-classified error labels, enabling a combined analysis that reinforces supervised learning.

The binary classification between faulty and correct events is then performed through dense layers, culminating in a sigmoid activation function. The model is trained using the binary cross-entropy loss function and optimized via the Adam algorithm. Performance evaluation is based on precision, with data split into training and test sets to ensure class balance and generalizability.

To enhance model performance, hyperparameter optimization is applied using TPE. The search process considers parameters such as embedding dimension, number of convolutional filters, convolutional kernel size, number of recurrent layer units, dropout rate, batch size, and number of training epochs, among others. The objective function aims to maximize the validation accuracy by selecting the most efficient configuration. After optimization, the hyperparameter values are stored and applied to the final model configuration, ensuring improved event classification performance. Fig. 3 illustrates the architecture of the optimized model for event classification.

The architecture presented in Fig. 3 illustrates the structured flow for event classification, which combines RCNN. The model begins with an embedding layer that transforms categorical or textual data into dense numerical representations. A one-dimensional convolutional layer (Conv 1D) then extracts local patterns, followed by a maximum pooling layer (MaxPooling 1D) that reduces dimensionality while preserving essential features. The resulting feature maps are passed to a GRU, which captures temporal dependencies by modeling sequential relationships among events. Subsequently, the recurrent output is concatenated with auxiliary inputs, specifically, pre-classified error labels, to enrich the representation before the decision stage.

In the classification phase, the combined features pass through dense layers, followed by a dropout layer that reduces the risk of overfitting. The final dense layer, activated by a sigmoid function, generates the binary classification output. This output is directed to a web interface composed of two modules: an operator panel for human-in-the-loop decision-making and an automated response logic for autonomous execution of substation actions. Two optimization processes are applied to enhance model performance: hyperparameter tuning is conducted prior to training using the TPE, while parameter optimization (weights and biases) occurs during training, with the Adam optimizer minimizing the binary cross-entropy loss.

3.6. *Protocol and event classification model validation*

The analysis and validation of the protocols is carried out through case studies covering different operational scenarios, including: (i) simple release with an open circuit breaker, (ii) simple release with an isolated circuit breaker, (iii) deenergized busbar, (iv) isolated busbar, (v) isolated transmission line, and (vi) isolated transmission line with completed span. During the release phase, the system evaluates the initial conditions of the equipment, ensures the correct execution of maneuvers, and issues the necessary authorizations to guarantee safety in the blocking of MB or the release of ML during the interlocking phase.

After defining the equipment states, classified as energized, deenergized, isolated, or grounded, the normalization phase begins, following the procedures established by the IMS. This process involves the removal of isolation and the reactivation of the equipment, always accompanied by authorizations issued by the TSO and the agents involved. Upon completion of the release and normalization phases, the system consolidates the maneuver documentation, validating the application of protocols across different operational scenarios in the power system (SEP). This ensures the safe execution of operations and efficient coordination among responsible agents.

The validation of the RCNN model is performed by analyzing performance metrics, including accuracy, precision, recall, and the F1 score. In addition, the confusion matrix is examined to assess the distribution of predictions between errors and correct classifications. The test set remains independent of the training data, ensuring the model's generalization capability.

To identify potential signs of overfitting or underfitting, the learning curve is analyzed, allowing the assessment of the model's performance evolution throughout training. Hyperparameter optimization, conducted using the TPE method, is compared to the baseline model to quantify the improvements achieved. The stability of the validation curve and the reduction in classification errors confirm the positive impact of the optimization process.

4. Results

This section presents the results obtained from the proposed methodology, applied to case studies in transmission lines. The evaluation considers the implementation of the automated control protocol for substation maneuvers and the influence of AI on error identification, operational optimization, and automated documentation. The performance of the RCNN model is analyzed in terms of event classification accuracy and error pattern detection. In addition, the impact of hyperparameter optimization and the reliability of predictions is discussed, evaluating the role of AI in enhancing automation and operational safety in substations.

4.1. *Substation characterization and computational implementation*

Based on the proposed methodology, a computational system is developed for the practical implementation of case studies. The protocol

Table 1
Configured equipment in BD_1 for testing.

Equipment	Quantity
Transmission Line	2
Transformer	1
Circuit Breaker	19
Disconnect Switch	54

is applied in the creation of the computational system, and BD_1 is initialized with the equipment specified in Table 1, including substations with break and breaker-and-a-half and ring bus topologies.

For the development of the case studies, data from Transmission Alliance of Electric Energy S.A. (TAESA), one of the largest power transmission companies in Brazil, were used. TAESA is involved in the construction, operation, and maintenance of transmission lines and substations in various regions of the country, playing a key role in the energy infrastructure sector. This study involves three substations: (i) Assis Substation, (ii) Londrina Substation, and (iii) Araraquara Substation. The Assis Substation (SEAS), located in western Sao Paulo, Brazil, operates at 525 kV, contributing to the reliability of the regional transmission system. Its geodetic coordinates are 22°39'42"S 50°25'06"W.

The Londrina Substation (SELO), located in the state of Parana, Brazil, connects the southern and southern power grids, operates with transmission lines of up to 525 kV and contributes to the balance of the energy distribution. Its geodetic coordinates are 23°18'37"S 51°09'46"W. The Araraquara Substation (SEAR), located in the interior of Sao Paulo, serves as a strategic high-voltage hub for Southeastern Brazil. It integrates 525 kV transmission lines and connects to other substations in partnership with Eletrobras Furnas. Its geodetic coordinates are 21°47'40"S 48°10'32"W. Since this study involves validation in a real system, in addition to TAESA's equipment, devices from other transmission operators that impact the performance of TAESA's infrastructure are also considered.

Fig. 4 presents aerial images of the Araraquara, Assis and Londrina substations, highlighting their physical structures and the arrangement of equipment such as transformers, reactors and transmission lines. Each substation has specific characteristics tailored to its role within the national interconnected system, with Assis Substation directly connecting to Araraquara and Londrina, while Londrina Substation is strategically important for integrating the Southern and Southeastern regions. The single-line diagram, which links the three substations, illustrates their interdependence and the 525 kV power flow, representing elements such as circuit breakers, disconnect switches and transformers. Integrating aerial images with the diagram provides a comprehensive view of the infrastructure, which is necessary to analyze and optimize switching operations in case studies.

4.1.1. Data integrity and audit mechanisms

Data integrity was considered an indispensable requirement for the reliable application of the AI model in critical infrastructure systems. In the proposed system, six distinct databases, BD_1 through BD_6, were used to organize and preserve operational information in a segregated and auditable manner. Each database served a specific function: BD_1 for the equipment topology, BD_2 for the initial conditions of the system, BD_3 for the switching sequence records, BD_4 for agent interactions and decision logs, BD_5 for the final control of the document and BD_6 for AI-based classification results. All write operations were monitored by an internal audit trail mechanism that automatically recorded timestamps, operator identifiers, and cryptographic hash-based verification codes, ensuring traceability, sequential integrity, and resistance to unauthorized modifications.

Although the system does not yet directly incorporate blockchain infrastructure, its architecture was designed to support the future implementation of immutable audit trails using distributed ledger technologies. This enhancement would enable cryptographic sealing of sensitive events, such as maneuver approvals, fault reclassifications, and manual interventions, thus increasing the reliability of records in high-criticality contexts. Meanwhile, the current audit mechanism has proven to be effective for real-time reconstruction of all procedural steps in the case studies, ensuring operational transparency and technical support for AI-driven decisions. The system's ability to preserve the fidelity of records, even under altered topologies or unplanned events, reinforces the robustness of the proposed solution.

4.2. Case Study 1: application of the release protocol

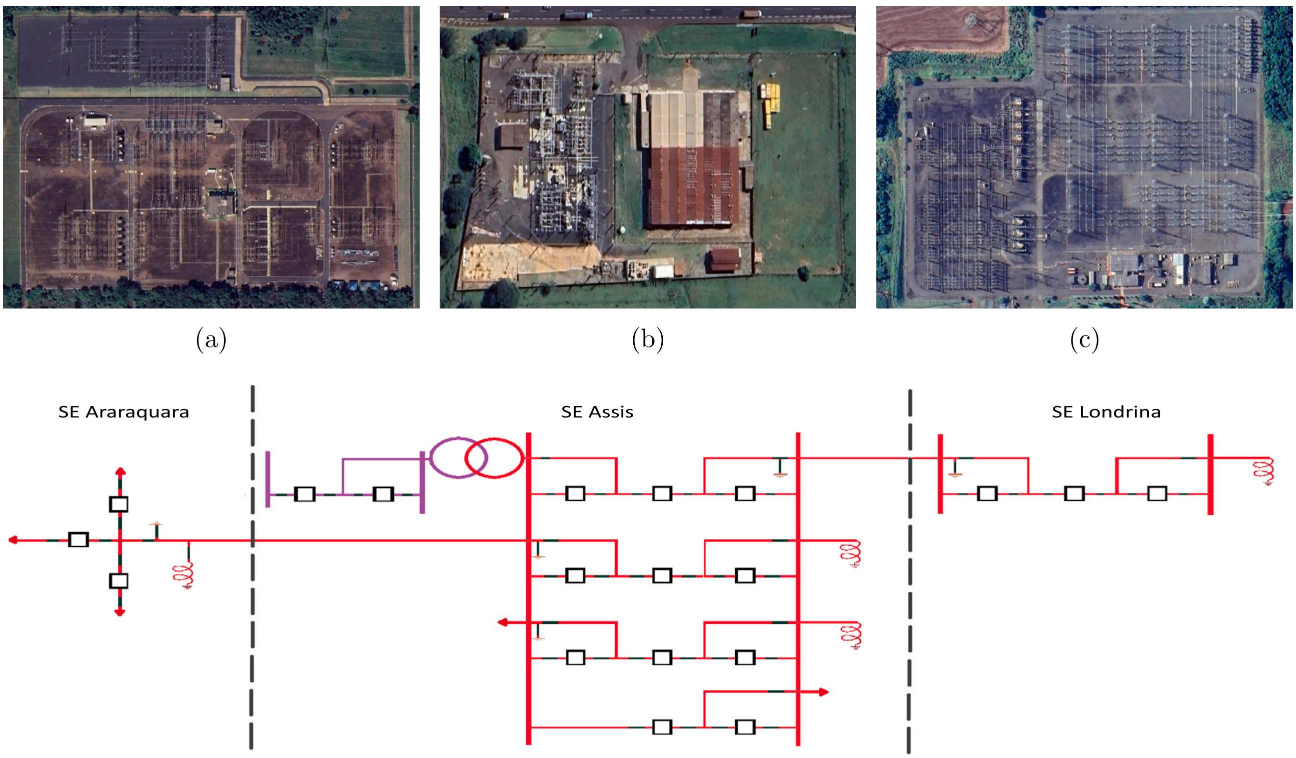
In this case study, a set of switching operations was performed both through simulation and physically at the SEAS and SELO substations, using the 525 kV Assis/Leondrina transmission line (TL), which connects the southern and southern regions of Brazil. The 525 kV sector of SEAS included four transmission lines, two reactors directly connected to the busbar, and a 525 kV/440 kV power transformer. The 525 kV sector of SELO consisted of seven transmission lines, three 525 kV/230 kV power transformers, and two reactors directly connected to the busbar. For a graphical representation of the single line diagram of the system, a static image was created to illustrate the simulated substations and the sections subject to modification, as shown in Fig. 5.

The system was developed using the Python programming language. The graphical interface was built with the `tkinter` library, and the databases BD_1, BD_2, BD_3, and BD_4 were managed using the `sqlite3` library. In BD_1, circuit breakers and disconnect switches were stored and organized according to the single-line transmission line diagram, ensuring that all equipment was available for operation at the start of the program. In the initial configuration and definition of interactive objects in the interface, circuit breakers and disconnect switches were represented as interactive buttons: circuit breakers as square buttons and disconnect switches as variable-sized buttons, depending on their position within the interface.

Each object was configured with the attributes `path` and `name`, which were used to identify and access the equipment. The switch of circuit breakers and disconnect switches was performed by modifying the `status` attribute to either the open or closed state. User interaction was facilitated through a command window that appeared when the desired equipment was selected, allowing the execution of commands via the `operar` button. The equipment state was visually represented by color: black for closed and white for open. Initially, all circuit breakers and disconnect switches were set to a closed state, while the grounding switches were kept open. After each command execution, the state of the new equipment was recorded in a `treeview` list, which also stored the operation timestamp using the `time` library.

The initial setup of the scenario and the execution of switching operations for the disconnection of the Londrina/Assis TL were first performed by setting all equipment as active, generating the BD_2 database upon activation of the `initial conditions` button. Subsequently, the disconnect maneuvers were performed by accessing the BD_1 database and opening circuit breakers D_1, D_2, D_3, and D_4. Following TL disconnect, isolation was implemented by opening disconnect switches K_1 and K_2. With the TL isolated, the grounding switches KT_1 and KT_2 were closed, and the disconnect switches were locked and marked with safety tags to indicate operation restriction. To complete the bay operation, the circuit breakers were closed again. Fig. 6 presents the single-line diagram of the TL in its isolated, grounded, and bay-complemented state. All switching operations were recorded in BD_3 by activating the `generate sequence` button. Table 2 presents the format of the document generated during the execution of the maneuver.

To define the equipment states, a specific function was implemented to analyze the maneuvers recorded in BD_3, classifying the state of the equipment based on the performed operations: (i) when the transmission line (TL) was deenergized, circuit breakers D_1, D_2, D_3, and D_4 were opened, registering the state as `deenergized`, (ii) when the TL



(d)

Fig. 4. Substation configuration: (a) Araraquara Substation, (b) Assis Substation, (c) Londrina Substation, and (d) single-line interconnection diagram of the substations.

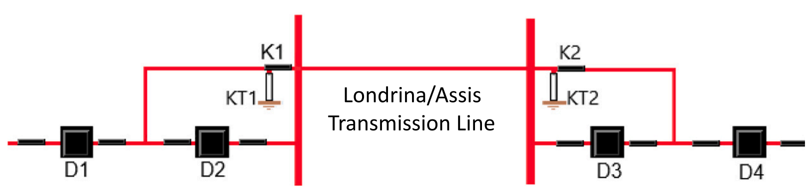


Fig. 5. Transmission line under initial conditions.

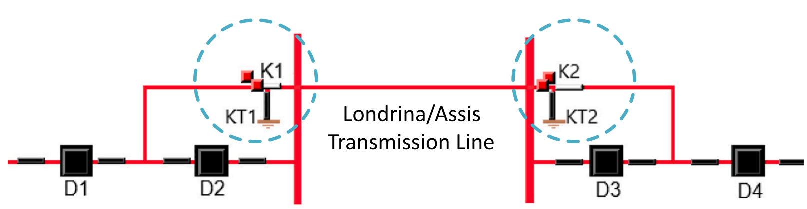


Fig. 6. Isolated, grounded transmission line and completed bay operation.

was isolated, the opening of disconnect switches K_1 and K_2 registered the state as `isolated`, (iii) when the TL was grounded, the closure of grounding switches KT_1 and KT_2 indicated the state as `grounded`, and (iv) the bay completion was performed by closing the circuit breakers at SEAS and SELO while maintaining the TL in an isolated state. These states were consolidated into a variable representing the Assis/Londrina TL as `deenergized`, `isolated`, or `grounded`, with bay completion. This variable was used in communication with the TSO.

To facilitate communication with the TSO and other agents, the system automatically generated the required text to request switching, isolation, and grounding maneuvers from the TSO, based on the state of the Transmission Function (TF). When a circuit breaker belonged to another agent, the system indicated the need for contact and sent a notification regarding the shared breaker maneuver. An operational message (OM) document was created using the `win32.Dispatch` library. The storage and export of maneuver data was centralized in the BD_4 database, which consolidated all variables generated throughout the operations. This database sequentially recorded interactions with the TSO, breaker and disconnect switch operations, bay completion, and exchanges with other agents. The stored information, including timestamps, document numbers, and service descriptions, was exported to a control file. The Web interface for generating the final report was developed in `TypeScript` with `ReactJS` and configured to retrieve data from BD_4, organizing them into a maneuver sequence similar to the printed format. The operator could review, add or remove commands before exporting the report, generating the BD_5 database for audit purposes.

Table 2
Sequence of switching operations performed in Case Study 1 release.

SE	Description	Time
COS	Request TSO authorization for the disconnection of the Londrina/Assis TL	07:02
COS	Receive TSO authorization for the disconnection of the Londrina/Assis TL	07:14
SE ASS	Open circuit breaker D4 at SE ASS	07:25
SE ASS	Open circuit breaker D3 at SE ASS	07:25
SE LON	Open circuit breaker D1 at SE LON	07:26
SE LON	Open circuit breaker D2 at SE LON	07:26
SE LON	Open disconnect switch K1 at SE LON	07:27
SE ASS	Open disconnect switch K2 at SE ASS	07:29
SE LON	Close grounding switch KT1 at SE LON	07:30
SE ASS	Close grounding switch KT2 at SE ASS	07:31
SE LON	Lock and place safety tag on disconnect switch K1 at SE LON	07:32
SE ASS	Lock and place safety tag on disconnect switch K2 at SE ASS	07:33
SE LON	Lock and place safety tag on grounding switch KT1 at SE LON	07:34
SE ASS	Lock and place safety tag on grounding switch KT2 at SE ASS	07:34
COS	Request TSO authorization to restore the Londrina/Assis TL bay	07:35
COS	Receive TSO authorization to restore the Londrina/Assis TL bay	07:37
SE ASS	Close circuit breaker D3 at SE ASS	07:38
SE ASS	Close circuit breaker D4 at SE ASS	07:38
SE LON	Close circuit breaker D2 at SE LON	07:40
SE LON	Close circuit breaker D1 at SE LON	07:40

Case Study 1 enabled a critical assessment of the release protocol under real and simulated operating conditions on the SEAS/SELO transmission line. The sequential standardization of switching procedures and the accurate identification of deenergized, isolated, and grounded states confirmed the consistency of the proposed model and its ability to ensure traceable transitions, thus facilitating communication with the TSO. The system architecture supported not only the safe execution of actions, but also the automated generation of operational documents and the structured logging of commands. The integration of databases BD_1 through BD_5 consolidated a replicable and auditable workflow, strengthening both the traceability and the reliability of the overall process.

However, the `tkinter` interface, while functional for training and testing purposes, exhibited limitations in scenarios involving multiple simultaneous interactions, which prompted the migration of the reporting module to a Web-based interface. This transition enhanced operator flexibility by enabling the review of command sequences prior to final export, underscoring the importance of solution adaptability. Furthermore, simultaneous manipulation of geographically distributed equipment exposed response delays in the graphical interface, highlighting the need for further optimization in critical environments. However, the protocol demonstrated resilience and generalization in different substations, meeting operational requirements for secure control of transmission assets.

4.3. Case Study 2: application of the normalization protocol

For the normalization process of the equipment switching operations at the SEAS and SELO substations, using the 525 kV Assis/Leondrina transmission line, the previously generated `sqlite3` file was employed. This file contained the maneuvers recorded in the BD_3 database during the release process. The execution of new maneuvers in the graphical interface for normalization was unnecessary, as all operations had already been performed in the release phase. Instead, querying the BD_3 database was sufficient. The sequence of maneuvers for normalization was then executed in reverse order of the release procedure IMS.

At the beginning of the normalization process of the transmission line (TL), it was confirmed that the span was complemented, with circuit breakers D_1, D_2, D_3, and D_4 closed and disconnected switches K_1 and K_2 open. Upon identification of the complemented span, a request was sent to the TSO to open the circuit breakers, allowing removal of isolation of the equipment. In cases where the circuit breaker was under the responsibility of another agent, a contact (DCVoA) was established using the same document generated during the release process, eliminating the need for a new document issuance. After alignment with the relevant agents, the maneuver order for span decomplementation was recorded (DMCV).

Using the database BD_3, the isolation of the equipment was verified according to the state protocol. The Londrina/Assis transmission line (TL) was confirmed to be isolated and grounded, with blocked disconnect switches (BdC). Consequently, the removal of the safety tag (DBCS) was recorded and the execution of the disconnect switch maneuver (DMCS) was initiated. Following removal of isolation, a new request was sent to the TSO (DDO) to make the Assis/Londrina TL available for reenergization. Then, the closure of the TL circuit breakers was executed (DMD). All information was consolidated in the normalization sequence of the database BD_6 and exported to the Web interface, allowing the operator to review, execute, and save the maneuvers, generating the final audit file in BD_5. Through the implementation of the normalization protocol, the TL was restored to its initial configuration, as illustrated in Fig. 5. Table 3 presents the format of the document generated during the maneuver.

Case Study 2 validated the normalization protocol in a scenario involving operational reversal after the complete release of the SEAS/SELO transmission line, using persistent records from the BD_3 database without requiring new manual maneuvers. The automatic recovery of the sequence, based on the reverse logic of the release procedure, preserved the integrity of the model by ensuring ordered transitions between the complemented, isolated and grounded states, triggering the unlocking and tag removal procedures according to operational standards. The integrated use of databases BD_3, BD_6, and BD_5 ensured the temporal consistency of commands, document consolidation, and audit file generation via the Web interface. In simulations with incomplete records or modified topologies, a limitation was observed in recognizing the initial state, indicating the need for adjustments in the verification logic. However, the protocol demonstrated resilience and adaptability, meeting the requirements for traceability and coordination of multiple agents even under modified conditions, enhancing its applicability to automated normalization processes in transmission systems.

4.4. Case Study 3: circuit breaker release

In this case study, the release of the circuit breaker D_1 was analyzed in SEAS, as illustrated in Fig. 7. The initial conditions considered all equipment operating under normal conditions. The release process involved the opening of the circuit breaker D_1, followed by the opening of the isolation disconnect switches K_1 and K_2, as well as local blocking

Table 3
Sequence of maneuvers performed during the normalization process in Case Study 2.

SE	Description	Time
COS	Request TSO authorization to decomplete the Londrina/Assis TL span	15:30
COS	Receive TSO authorization to decomplete the Londrina/Assis TL span	15:35
SE ASS	Open circuit breaker D4 at SE ASS	15:36
SE ASS	Open circuit breaker D3 at SE ASS	15:36
SE LON	Open circuit breaker D1 at SE LON	15:37
SE LON	Open circuit breaker D2 at SE LON	15:38
SE LON	Unblock and remove safety tag from disconnect switch K1 at SE LON	15:39
SE ASS	Unblock and remove safety tag from disconnect switch k2 at SE ASS	15:39
SE LON	Unblock and remove safety tag from disconnect switch kT1 at SE LON	15:40
SE LON	Unblock and remove safety tag from disconnect switch kT2 at SE ASS	15:41
SE LON	Open disconnect switch KT1 at SE LON	15:41
SE ASS	Open disconnect switch KT2 at SE ASS	15:42
SE LON	Close disconnect switch k1 at SE LON	15:45
SE ASS	Close disconnect switch k2 at SE ASS	15:47
COS	Make the Londrina/Assis TL available to TSO	16:02
COS	Receive TSO request to energize the Londrina/Assis TL	16:08
SE LON	Close circuit breaker D2 at SE LON	16:10
SE LON	Close circuit breaker D1 at SE LON	16:11
SE ASS	Close circuit breaker D3 at SE ASS	16:12
SE ASS	Close circuit breaker D4 at SE ASS	16:12

Table 4
Sequence of operations performed for Case Study 3 clearance.

SE	Description	Time
COS	Request TSO authorization to open and isolate circuit breaker D1 at SE ASS	16:25
COS	Receive TSO authorization to open and isolate circuit breaker D1 at SE ASS	16:28
SE ASS	Open circuit breaker D1 at SE ASS	16:29
SE ASS	Open isolating switch K1 at SE ASS	16:30
SE ASS	Open isolating switch K2 at SE ASS	16:31
SE ASS	Lock and place a safety tag on isolating switch K1 at SE ASS	16:31
SE ASS	Lock and place a safety tag on isolating switch K2 at SE ASS	16:31

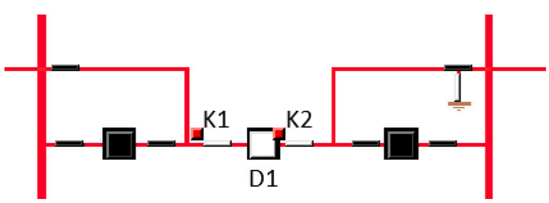


Fig. 7. Isolated circuit breaker.

and the application of a safety tag on both switches. The maneuver was executed through the system's graphical interface and exported to the Web interface, generating the isolation and normalization sequences. Interactions with the TSO and other agents were properly recorded. Table 4 presents the format of the document generated during the maneuver.

Case Study 3 provided a controlled environment to assess the performance of the protocol in the release of an individual circuit breaker under nominal operating conditions. The simplicity of the topology involved facilitated the verification of state transitions, and the shutdown sequence, which comprises the opening of the circuit breaker D_1 and the isolation of switches K_1 and K_2, followed by local locking and safety tagging, was consistent with the established protocol criteria. Although the absence of topological constraints reduced the need for interlocking validation, the system effectively classified and documented each step, reinforcing its applicability in structured operations. A noted limitation was the lack of real-time synchronization between the graphical status and the internal system records, which, although not critical in this specific case, may pose risks in more complex scenarios or during concurrent operations. Therefore, this case highlighted the procedural reliability of the protocol while also indicating the need for improvements in state monitoring and visual feedback to ensure resilience in more demanding contexts.

4.5. Case Study 4: busbar clearance in a substation shared by multiple agents

In this case study, SEAS was used for busbar isolation B_1. The primary objective was to analyze the results of switching operations involving multiple transmission agents. Fig. 8 presents two transmission agents, OA1 and OA2. Initially, a request for busbar disconnect B_1 was submitted to the TSO. Subsequently, the agents OA1 and OA2 were requested to open circuit breakers D_3 and D_4 by issuance of an impediment authorization document.

The busbar isolation was carried out independently by each agent through the opening of their respective circuit breakers and disconnect switches. All switching operations and their respective coordination steps were systematically recorded in the maneuver sequence. The normalization process followed the expected procedure, including the removal of isolation by the requesting transmission agent, the request and execution of maneuvers by agents OA1 and OA2, a subsequent request to the TSO for busbar energization, and finally the closing of the busbar circuit breakers. Table 5 presents the format of the document generated during the release maneuver.

Case Study 4 enabled a critical evaluation of the performance of the protocol in a collaborative context, in which the isolation of the busbar B_1 at the SEAS substation involved multiple transmission agents. Unlike previous studies, this scenario introduced additional organizational complexity, requiring sequential confirmations from OA1 and OA2 after the initial request of the responsible agent. Although the logic of the protocol was executed correctly – with the issuance of clearance orders, structured logging, and assured traceability – operational data indicated that the total execution time was significantly affected by latency in agent responses.

The protocol's efficiency in this type of scenario depends not only on internal automation, but also on the responsiveness of external agents. The graphical interface supported a clear visualization of agent responsibilities, but the absence of escalation mechanisms or inactivity

Table 5
Sequence of switching operations performed in Case Study 4.

SE	Description	Time
COS	Request TSO approval to deenergize and isolate B1 at SE ASS	10:59
COS	Receive TSO authorization to deenergize and isolate B1 at SE ASS	11:00
SE ASS	Open D1 at SE ASS	11:01
SE ASS	Open disconnector K1 at SE ASS	11:02
SE ASS	Open disconnector K2 at SE ASS	11:03
SE ASS	Lock and place a safety tag on disconnector K1 at SE ASS	11:04
SE ASS	Lock and place a safety tag on disconnector K2 at SE ASS	11:04
COS	Request OA1 to perform isolation procedures on D1 at busbar B1 at SE ASS	11:05
COS	Request OA1 to perform isolation procedures on D2 at busbar B1 at SE ASS	11:05
COS	Request OA2 to perform isolation procedures on D3 at busbar B1 at SE ASS	11:08
COS	Request OA2 to perform isolation procedures on D4 at busbar B1 at SE ASS	11:08
COS	Receive confirmation from OA1 regarding the isolation of D1 at busbar B1 at SE ASS	11:20
COS	Receive confirmation from OA1 regarding the isolation of D2 at busbar B1 at SE ASS	11:20
COS	Receive confirmation from OA2 regarding the isolation of D3 at busbar B1 at SE ASS	11:25
COS	Receive confirmation from OA2 regarding the isolation of D4 at busbar B1 at SE ASS	11:25

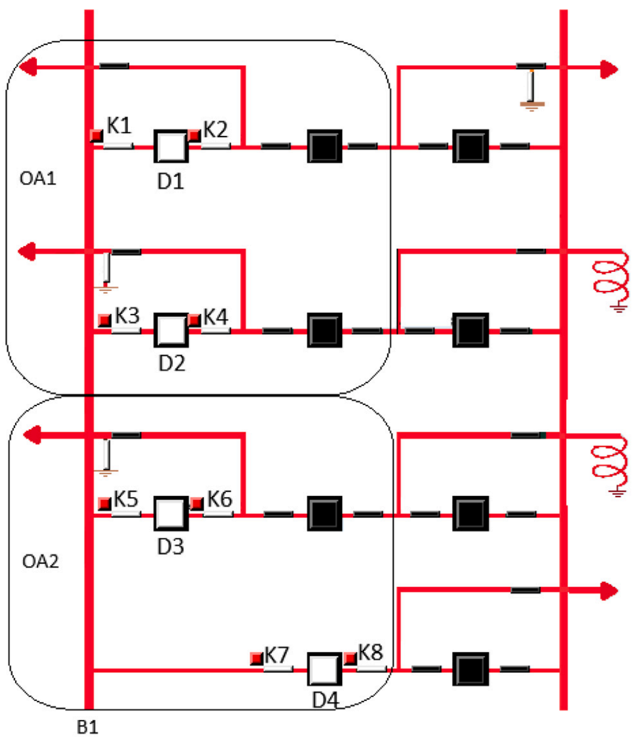


Fig. 8. Busbar isolation.

alerts limited the operator's ability to intervene during delays. Therefore, although the protocol demonstrated resilience and procedural compliance, the findings pointed to the need for enhancements such as latency monitoring, asynchronous communication, and automated notifications to strengthen its applicability in critical environments with distributed operational control.

4.6. Case Study 5: transformer release after contingency

In this case study, a 525 kV/440 kV transformer was used. The activation of the transformer protection system was simulated by manually opening the circuit breakers D_1, D_2, D_3, and D_4 through the graphical interface, considering them open under initial conditions. Subsequently, transformer isolation maneuvers were executed by opening disconnect switches K_1, K_4, K_5, K_6, K_7, and K_8, as illustrated in Fig. 9.

In this scenario, since the transformer was already deenergized due to protection activation, there was no need to request a shutdown from the TSO. The equipment described in the initial conditions was not included in the release request to the TSO, and the sectionalization switch operations, as well as the insertion of safety locks, were automatically executed after the maneuvers were performed at the interface. For the normalization process, a request was sent to the TSO for transformer energization, as its reintegration into the system depends on this authorization.

The system was developed based on the principles of the SCADA system, enabling the execution of equipment commands upon confirmation, the generation of timestamps recording the operation times, and the creation of a database equivalent to that of the real supervision and control system. Thus, in a potential implementation, the real-time operation system can replace the proposed interface, fully utilizing the database of the currently used system. To execute the proposed protocol, it is only necessary to correctly indicate the shared equipment from the Control Center (CO) or other agents (OA). Table 6 presents the format of the document or file generated during the execution of the maneuver, which will be used for AI pattern recognition.

The normalization operation in Case Study 5 allowed for the assessment of the protocol's performance in a scenario with low topological complexity, but under atypical contingency conditions. The requirement for transformer reenergization approval highlighted the need to align automated flows with the regulatory procedures defined by the TSO. In addition, the absence of energized circuit breakers in the initial stage reduced the demand for interlock verification, simplifying execution. This context facilitated the validation of aspects such as temporal consistency of commands, accuracy of records, and the system's ability to operate with integrity following unplanned events. The precision in reconstructing the sequence using databases BD_3, BD_5 and BD_6 indicated that the protocol maintained satisfactory performance even when applied to degraded topologies. This operational resilience is particularly relevant in substations subject to complex contingencies or involving multiple agents.

4.7. Generation of files for error classification

After validating the simulator, correct and erroneous maneuvers were generated to train the AI model. This process resulted in the creation of 54 files containing errors and 54 error-free files. Each file followed a structured format with columns, as described in Table 2 through Table 6. The columns were organized as follows: the first column corresponds to the identification of substations, the second provides a description of the executed task, the third records the event's timestamp, the fourth represents the classification label, where 0 indicates a correct event, 1 denotes an error, and the fifth specifies the reason for the error, when applicable.

The raw data was subjected to a preprocessing phase to ensure standardization and integrity before modeling. Mandatory columns were verified, diacritics and special characters were removed, and all

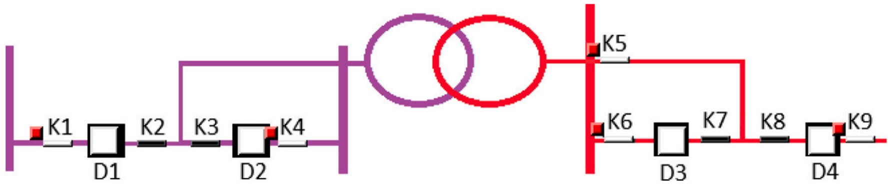


Fig. 9. Transformer isolation after contingency.

Table 6
Sequence of maneuvers performed in Case Study 5.

SE	Description	Time
COS	Request TSO authorization for the isolation of TR5 at SE ASS	07:09
COS	Receive TSO authorization for the isolation of TR5 at SE ASS	07:17
SE ASS	Open isolating switch k1 at SE ASS	07:18
SE ASS	Open isolating switch k4 at SE ASS	07:19
SE ASS	Open isolating switch k5 at SE ASS	07:20
SE ASS	Open isolating switch k6 at SE ASS	07:22
SE ASS	Open isolating switch k9 at SE ASS	07:24
SE ASS	Lock and place a safety tag on isolating switch k1 at SE ASS	07:25
SE ASS	Lock and place a safety tag on isolating switch k4 at SE ASS	07:26
SE ASS	Lock and place a safety tag on isolating switch k5 at SE ASS	07:27
SE ASS	Lock and place a safety tag on isolating switch k6 at SE ASS	07:28
SE ASS	Lock and place a safety tag on isolating switch k9 at SE ASS	07:28

text was converted to lowercase. The event timestamp column was standardized to a *timestamp* format, and the intervals between consecutive events were calculated and stored in a new column named interval. Throughout this process, structural consistency was maintained, classifying records as errors or correct based on the values in the label column. For files classified as correct, where the reason column was absent, it was automatically generated and filled with zeros. Upon completion of these steps, the processed files were stored in `.csv` format, ensuring the necessary standardization for the subsequent analysis stages.

The next step involved organizing and refining the files by removing the reason column, when present, and extracting its unique values, which were then mapped to the corresponding file names. This information was consolidated into a dictionary that contains the identification of each file and its respective error reason, ensuring the uniformity of the data and facilitating processing in subsequent stages. After extracting the error reasons and building the dictionary, the files were updated and stored in a new directory. Subsequently, a library was compiled that includes approximately 30 potential errors that were not previously recorded in the dictionary. Finally, both the extracted error dictionary and the library of potential errors were structured into a dataframe and stored in the file `combined_rules.pkl`. This process unified the extracted error dictionary with predefined rules, ensuring the necessary standardization for data analysis.

The consolidation of information in the file `combined_rules.pkl` involved a standardization process, eliminating unnecessary spaces and ensuring compatibility with the UTF-8 format. Consequently, the data were structured systematically, allowing efficient information retrieval and precise application of rules to the analyzed events, thus enhancing the reliability of the detection process. Following this step, the files were processed, their textual information was converted into tokenized sequences, and numerical variables were extracted and normalized using `StandardScaler`, ensuring compatibility with the format adopted for model training.

To identify patterns in the events, the files were analyzed in segments using sliding windows of three consecutive records. This approach enabled the extraction of temporal patterns and increased the number of instances available for model training. Consequently, class balancing was required and was performed using the `SMOTETomek` technique, ensuring a homogeneous distribution between errors and correct instances, thus creating a representative data set. The combined application of these techniques allowed a single file to generate multiple training samples, improving the diversity of the data set and improving the generalizability of the neural network. Fig. 10 illustrates the structure of the sliding window, based on Table 4, which corresponds to Case Study 3.

For external validation, 15% of the data was reserved by randomly selecting a subset of pre-processed files, which were stored in a designated folder. The selection process ensured an equitable distribution across the files, guaranteeing that at least one contained **error** records and at least one contained **correct** records. For each selected file, the label column, which indicated whether the recorded events were **errors** or **correct**, was removed to prevent potential biases in the validation process. To maintain traceability, a document was generated to record the correspondence between the processed files and their new identifiers for validation. The files were renamed following a sequential pattern and the mapping between the original and new names was documented in `key.txt`, ensuring a neutral validation process free from the influence of the original labels.

4.8. Application of AI in error classification

A RCNN model was developed to identify error patterns in operational records. The process involved preprocessing input files, structuring event sequences, applying transformations to textual and numerical data, and training the model with parameter and hyperparameter optimization. The objective was to improve error detection and ensure the representativeness of the patterns extracted from the records. The use of a sliding window comprising three consecutive events enabled the identification of temporal patterns associated with errors. This procedure facilitated the contextual analysis of events and the accurate assignment of classification labels.

In this application, two optimization methods were employed. The network was optimized using the Adam algorithm, a gradient descent optimizer that adjusts weights and biases during training, reducing prediction errors over iterations, and minimizing the binary cross-entropy loss function. The hyperparameters and parameters of the model were tuned using the TPE, which evaluates different configurations of models over multiple runs to identify the combination that maximizes the accuracy of the validation. The TPE optimization process included tuning the embedding dimension, the number of convolutional filters, the kernel size, the number of units in the GRU layer, the dropout rate, the batch size, and the number of training epochs. The objective function of TPE was designed to maximize the accuracy of the validation, ensuring

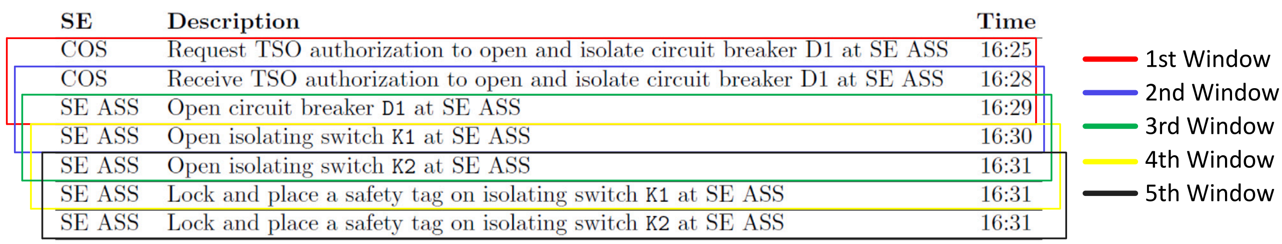


Fig. 10. Illustration of sliding windows.

Table 7
Optimized hyperparameters and parameters for RCNN model training.

Hyperparameter	Value
Embedding dimension e_d	87
Number of filters n_f	34
Kernel size k_s	4
GRU units rnn_u	31
Dropout rate d_r	0.3510
Batch size b_s	41
Number of epochs e	40
Maximum vocabulary size M_w	15 000
Maximum sequence length M_{sl}	100
Sliding-window size S_w	3
Pre-output dense layer U_{ed}	True

that the final configuration of the hyperparameter and the parameters achieved optimal performance. Table 7 presents the optimized values of these hyperparameters and parameters, which results in a model with improved predictive capacity and a lower risk of overfitting.

In Table 7, the parameters M_w, M_{sl}, and S_w are specific to the RCNN model, directly influencing textual data processing prior to training. These parameters correspond to the maximum number of words considered in the vocabulary, the maximum sequence length of processed words, and the number of consecutive events used in the sliding-window construction, respectively. The parameter U_{ed} = True indicates the inclusion of an additional dense layer before the network output, allowing a refined representation of the features extracted by the previous layers. This layer improves the ability of the model to integrate relevant characteristics, improving the efficiency of learning in the prediction stage.

The training process produced an optimized model, stored in the `.keras` format, enabling its reuse and future application. Among the aspects analyzed, the evolution of the accuracy over epochs was observed. Fig. 11(a) illustrates this progression, showing an initial increase in precision during the first iterations until it stabilized at approximately 80% for both the training and test sets. The stability of the validation curve suggests that the model generalized well without signs of overfitting, reinforcing the consistency of the hyperparameter optimization strategies employed.

Fig. 11(b) compares the final accuracy of the baseline and optimized models. The key distinction between them lies in the absence of hyperparameter optimization in the baseline model, leading to lower accuracy, a higher risk of overfitting, and reduced generalization capability. Although the baseline model achieved an approximate accuracy of 70%, the optimized model demonstrated superior performance, reaching around 82%. These findings indicate that the applied optimization strategy significantly improved the predictive capacity of the model. The hyperparameter adjustment had a positive impact on the accuracy of the classification, allowing the optimized model to identify patterns with greater precision and stability throughout the training.

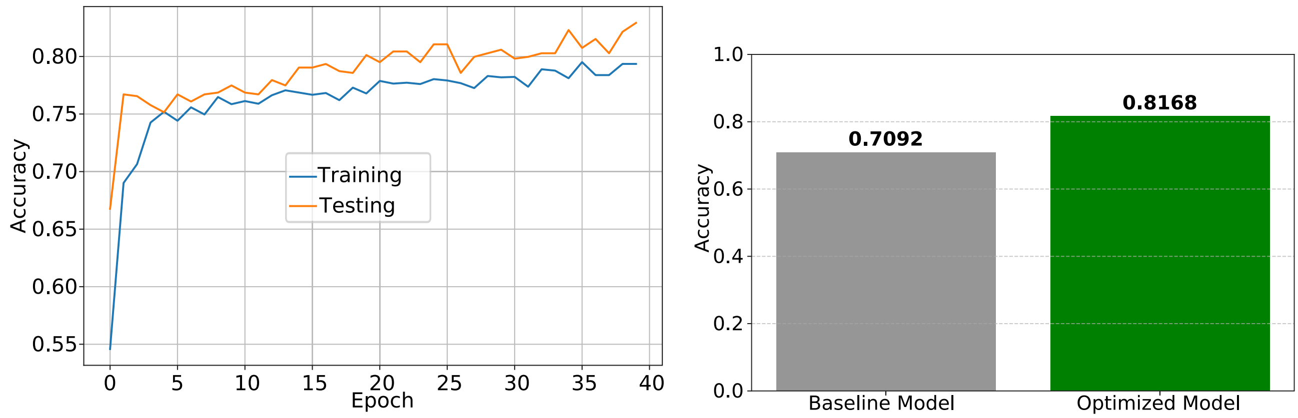
The trained neural network achieved a final accuracy of 82.92% on the test set, correctly classifying the majority of evaluated events. However, when evaluating class balance, the model obtained an F1-score of 78.6% for errors, with a precision of 83.96% and a recall of 81.37%. This indicates that while the model accurately classifies most errors, it still produces false negatives. Fig. 12(a) presents the confusion matrix of the trained model, illustrating the distribution of correct and incorrect predictions. A total of 262 errors were correctly identified, while 60 errors were misclassified as correct events. Furthermore, 50 error-free events were incorrectly classified as errors, suggesting that the model prioritizes minimizing false positives but still requires improvements to reduce the false negative rate. This indicates that while the model accurately classifies most errors, it still produces false negatives. Table 8 summarizes the main performance metrics obtained in the test set, including class-specific measures.

Fig. 12(b) illustrates the relationship between the actual labels and the prediction of the model. The distribution of predictions is mainly concentrated at the extremes, near 0 and 1, indicating that classification is predominantly binary with low ambiguity, which aligns with the nature of the problem. The proximity between the actual and predicted distributions suggests that the model adequately captured the data structure, despite slight variations in the density of intermediate values. This behavior is consistent with the confusion matrix, reinforcing the stability of the model's performance. However, improvements are necessary to reduce the false negative rate and improve the precision of identifying actual errors.

Table 9 presents the percentage values for true negatives (TN), false positives (FP), false negatives (FN), and true positives (TP), corresponding to the confusion matrix illustrated in Fig. 12(a). The distribution of results indicates satisfactory model performance, although a significant number of errors remain undetected, highlighting the need for adjustments to minimize FN without compromising precision. A detailed analysis of precision and recall reinforces this trend, as the model correctly predicts an error in 83.96% of cases but does not identify 18.63% of actual errors.

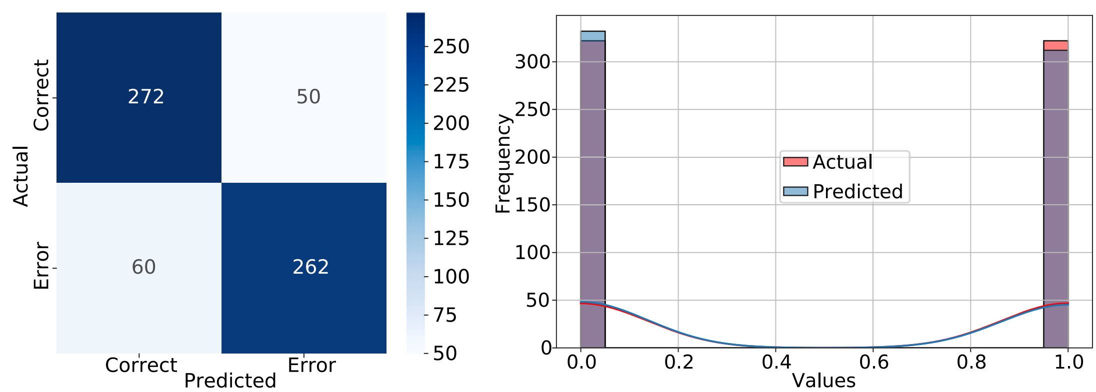
Considering the limited size of the training dataset, which consisted of 108 files (54 containing errors and 54 without errors), the model exhibited satisfactory performance. The difference between the 108 original files and the 644 samples used in the confusion matrix results from the segmenting of events into sliding windows of three consecutive records, as illustrated in Fig. 10. This procedure enabled the capture of temporal patterns and increased the number of instances available for training. Furthermore, the application of the `SMOTETomek` technique allowed a single file to generate multiple samples, improving the representativeness of the data and increasing the diversity of the model. For example, a file containing 20 events could generate up to 18 distinct sequences, significantly expanding the training data set. The underlying logic of this technique considers each sliding window as a representation of either **error** or **correct**, allowing the model to sequentially learn the patterns associated with each class.

The `SMOTETomek` technique combined synthetic sample generation with redundancy removal, resulting in a more homogeneous dataset, as illustrated in Fig. 12(b). Sequential modeling, combined with predefined rules, enhanced pattern detection, reducing the incidence of false positives and false negatives. The integration of recurrent and CNNs proved effective in extracting textual features and temporal patterns from operational events. The optimization process was repeated 15 times to ensure greater accuracy in the average time calculation, yielding a total processing time of 2 h, 5 min and 26 s for data preparation



(a) (b)

Fig. 11. Training analysis: (a) accuracy evolution during training and (b) comparison between the baseline and optimized models.



(a) (b)

Fig. 12. Training analysis: (a) confusion matrix of the training process and (b) distribution of model predictions concerning actual labels.

Table 8
Summary of performance metrics for the trained model.

Metric	Value [%]	Remarks
Accuracy	82.92	Global accuracy of the model on the test set
Precision	83.96	Computed for the error class (positive class)
Recall	81.37	Computed for the error class
F1-score	78.60	Harmonic mean between precision and recall for the error class

Table 9
Confusion matrix percentages for the trained model.

	Class 0 (Correct)	Class 1 (Error)
Actual: 0	42.24% TN	7.76% FP
Actual: 1	9.33% FN	40.67% TP

and model adjustment, followed by 1 min and 43 s for training and approximately 1 s for testing and prediction.

To enhance the evaluation of the performance of the model, representative patterns of false positives and false negatives were analyzed. As shown in Fig. 12(a) and Table 9, the RCNN achieved an overall accuracy of 82.92%, with 262 true positives and 272 true negatives. However, it also generated 60 false negatives and 50 false positives. False positives typically occurred in sequences involving rapid, yet valid switching operations, especially those with unusually short time intervals or incomplete textual descriptions. These features aligned with known heuristic indicators of faulty behavior, prompting the model to misclassify such instances as errors. In contrast, false negatives were frequently associated with events that included standard textual descriptions but concealed atypical state transitions or interlocking violations. These cases were often overlooked due to their underrepresentation in the training dataset.

These findings suggest that the RCNN is sensitive to incomplete contextual information and linguistic ambiguity in operational records. To mitigate these issues, two countermeasures were implemented. First, a rule-based enrichment procedure was employed during data preprocessing to simulate edge-case behaviors and improve the diversity of error classes. Second, an interpretive alert system was embedded in the inference stage. This system emits contextual warnings whenever input sequences deviate from expected spatio-temporal configurations, such as abnormal timing patterns or inconsistent equipment states, even in the absence of an explicit error classification. These mechanisms improve operator awareness and improve system resilience in borderline scenarios.

4.8.1. Operational database integration for error classification

The RCNN developed in this study was integrated with the set of operational databases, BD_1 to BD_6, allowing inference of errors based on events extracted from the system. During training, the input data was structured from previously validated maneuver sequences, incorporating equipment topology from BD_1, interlocking logic from BD_4, and event history from BD_3. Input vectorization account for the physical arrangement of equipment and the chronological order of operations, preserving the logical sequence of events. To capture temporal patterns, a sliding window segmentation of three events was applied. Although a single log could generate multiple samples, each instance preserved a specific interval between events and a distinct context, ensuring the statistical independence of the labels. Subsequent analysis of model residuals and predictive score distributions confirmed the absence of bias due to excessive overlap, thus reducing overfit risk.

To address class imbalance, particularly due to the low frequency of actual operational errors, the `SMOTETomek` technique was applied, combining synthetic oversampling with the removal of ambiguous instances. Quantitative analysis indicated a reduction in false negative rates and the preservation of overall accuracy, without a significant increase in false positives, suggesting improved generalization. Furthermore, the final distribution of the model scores showed clear separability of the classes, which reinforced the effectiveness of the balance strategy. During the inference phase, the RCNN received input vectors formatted according to the IEC 61850 specifications (International Electrotechnical Commission, 2020), enabling interoperability with legacy systems and seamless integration with existing automation devices.

Events classified as errors trigger, in real time, warning signs recorded in BD_6. These flags activated dynamic interlocking mechanisms based on the rules defined in BD_4 and the monitored equipment states stored in BD_2, resulting in automatic blocking of commands inconsistent with the current substation conditions. The complete inference process, including sequence reading, vectorization, prediction, validation, and response, was completed in an average time of approximately one second per sequence. This performance confirms the suitability of the model for operational environments that require real-time response.

4.8.2. Comparative analysis with alternative classifiers

The choice of GRU over LSTM in the RCNN model was guided by computational performance considerations and suitability for deployment in environments with strict response time constraints, such as transmission substations. Although both architectures are capable of modeling temporal dependencies in event sequences, previous studies indicate that GRUs, due to their simpler structure and the reduced number of parameters, tend to converge faster while achieving comparable performance in sequential classification tasks (Zhou et al., 2024; Cahuantzi et al., 2023). This characteristic was a key factor in integrating the network into the real-time inference system, reducing computational costs without compromising accuracy.

In addition to the comparison with the non-optimized baseline model, two conventional classifiers were evaluated: Random Forest (RF) and Support Vector Machine (SVM). Both were applied to the same vectorized samples obtained from sliding windows and subjected to identical normalization procedures. The RF model achieved an accuracy of 74.62% and an F1-score of 69.10%, while the SVM showed lower performance, with an accuracy of 71.35% and an F1-score of 66.81%. Although satisfactory, these models exhibited limited ability to capture temporal patterns within sequences, particularly in events involving partial contextual overlap. The optimized RCNN outperformed both alternatives, reaching a final accuracy of 81.72% and an F1-score of 78.60%, with greater consistency in detecting events classified as errors. Fig. 11(b) illustrates the improvement over baseline, while Table 10 summarizes the comparative quantitative indicators. These findings underscore the suitability of the GRU-based RCNN for the proposed task, balancing precision, execution time, and compatibility with operational processes in substations.

Table 10
Comparative performance of classifiers in operational error detection.

Model	Accuracy [%]	F1-score [%]
RF	74.6	69.1
SVM	71.3	66.8
RCNN Optimized	82.9	78.6
RCNN baseline	70.9	–

4.9. Validation of the proposed method

The validation of the automated protocol was carried out through practical implementation in a simulation environment, employing five case studies representative of different operational scenarios in transmission substations. These studies encompassed the application of the protocol to release, interlocking, normalization, and complementation maneuvers, ensuring compliance with operational and safety guidelines. The simulator was configured to replicate the real conditions of the SEAS, SELO, and SEAR substations, considering distinct topologies and the interaction between multiple transmission agents.

The test structure followed the proposed methodology, in which each case study was executed through the computational interface and applied to real substations. The maneuvers were performed and compared to standard operating procedures, ensuring that the actions of the system were in accordance with the requirements of the electrical sector. The records generated by the simulator were analyzed for accuracy in operation execution, compliance with TSO regulations, and coherence in maneuver sequencing, validating the integrity and reliability of the protocol.

The tests confirmed that the system accurately executed the maneuver sequences, meeting safety requirements and ensuring proper interlocking between equipment. The simulator automatically generated the necessary authorizations for each operational stage, recorded execution times, and ensured the complete traceability of actions. Furthermore, the normalization process was validated by comparing the initial and final states of the equipment, ensuring that the simulation faithfully reproduced the expected operational conditions.

The audit of the records confirmed that all interactions with transmission agents were properly documented, including the exchange of information between the TSO and other involved operators. The maneuver sequencing strictly followed the established workflow, with no inconsistencies in the operational logic, indicating that the automated protocol can be reliably applied as a support system for substation operations.

After the internal validation, which included model training and testing, an external validation of the proposed solution was performed. For this procedure, 15% of the previously reserved files were used for validation, totaling 17 files that were not included in training or testing. The validation was carried out over 15 optimization rounds with the aim of evaluating the average processing time and the performance of the model. The results indicated that, over multiple rounds, the neural network correctly classified most events, maintaining a consistent accuracy rate in detecting **errors** and **correct actions**. Table 11 presents the comparison between the actual labels and the model predictions throughout the 15 validation rounds, as well as the error deviation, given by:

$$D_E = \left[\frac{(A_R + E_R) - (A_P + E_P)}{A_R + E_R}\right] \cdot 100 \tag{1}$$

In (1) and Table 11, D_E represents the percentage error deviation, A_R denotes the actual correct labels, E_R the actual error labels, A_P the predicted correct labels and E_P the predicted error labels. The values in Table 11 align with the trends observed in the internal validation, with error deviation ranging from −17.64% to 0%. Negative values indicate that the model underestimated the number of actual errors, while 0% corresponds to exact predictions. The results suggest that the model maintained consistent performance, correctly classifying most

Table 11
External validation over 15 rounds.

Round	Actual labels		Model predictions		D_E [%]
	A_R	E_R	A_P	E_P	
1	3	14	2	12	−17.64
2	5	12	5	12	0.00
3	7	10	6	10	−5.88
4	8	9	8	9	0.00
5	1	16	1	16	0.00
6	9	8	8	7	−11.76
7	10	7	10	7	0.00
8	7	10	7	9	−5.88
9	6	11	6	10	−5.88
10	8	9	8	8	−5.88
11	9	8	8	7	−11.76
12	4	13	4	12	−5.88
13	2	15	1	14	−5.88
14	9	8	7	8	−11.76
15	6	11	6	11	0.00

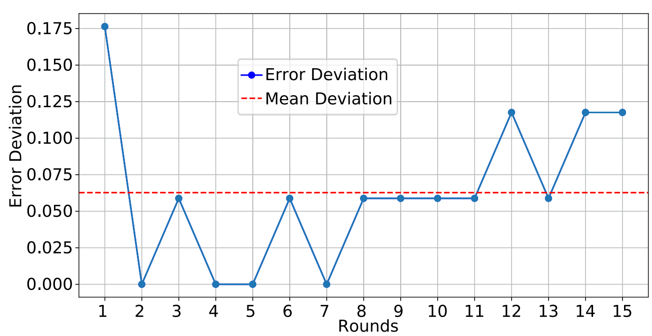


Fig. 13. Error deviation per round in external validation.

of the events throughout the validation rounds. However, a tendency to underestimate false negatives was observed, as reflected in slightly lower predicted error counts in some iterations. Overall, the results of the external validation confirm the model's ability to generalize to new data, reinforcing its applicability for detecting operational errors in transmission substations.

Fig. 13 illustrates the variation in error deviation over 15 rounds of external model validation. Although some rounds exhibited significant fluctuations, others did not, indicating that the model maintained consistency in most executions. The average error deviation in all rounds was 6.27%, as represented by the red dashed line on the graph. This value reflects the mean relative error between the actual labels and the model predictions, demonstrating the stability of the proposed solution in identifying operational patterns.

Based on the analysis of the presented results, the developed model demonstrated generalizability when tested with data not used during training. External validation confirmed the stability of its performance, as indicated by the low variation in error deviation between validation rounds. Although the model exhibited a slight tendency to underestimate errors, the average deviation of 6.27% suggests that, in most executions, the predictions remained consistent with the actual labels. These findings reinforce the feasibility of applying the proposed solution for the automated identification of operational errors in transmission substations, contributing to improved operational safety and efficiency.

4.9.1. Comparison between traditional and automated protocols

The comparative analysis indicates that traditional methods to execute and record operational maneuvers exhibit structural limitations that hinder traceability, reproducibility, and integration with supervisory systems. Approaches based on spreadsheets, printed forms, and manual workflows are highly dependent on the operator's experience and require human verification at multiple critical points, making it difficult to track actions and simulate operational scenarios. In certain routines, more than 100 fragmented manual actions may be required, exposing the process to frequent naming inconsistencies and a lack of automated validation (Ockwell, 2014).

In contrast, the automated protocol developed in this study structures the sequential execution of maneuvers through a graphical interface linked to structured databases, incorporating state transition control, standardized document generation, and real-time validation. The integration of RCNN classifiers into the process enabled the automatic identification of operational patterns and failures, even under varying topological conditions. Table 12 summarizes the key differences between traditional methods and the proposed solution.

Complementarily, the comparison with formal approaches such as Petri nets and rule-based expert systems highlighted relevant differences in terms of generalization and adaptability. Although symbolic models provide a formal structure for well-defined processes, they tend to face limitations in interpreting events with temporal variability and incomplete information. In this study, an indirect modular approach was adopted, inspired by proposals such as Lei et al. (2023) and Lei et al. (2025b), by structuring the databases as interpretable units with temporal mapping and cross-validation of events. This architecture supported not only technical performance, but also enhanced transparency and auditability in the automated decision-making process.

4.10. Advanced validation, interpretability, and operational constraints

This stage of the study focused on the advanced evaluation of the proposed solution, considering the efficiency of hyperparameter optimization, the robustness of quantitative metrics, the limits of model interpretability, computational requirements in operational environments, and mechanisms for handling failures and conflicts. Each aspect was examined based on the experiments already conducted, with the aim of deepening the evaluation of the automated protocol and demonstrating its practical applicability in real-world transmission substation scenarios. To this end, sub-sections were organized to address the hyperparameter optimization strategy, with an emphasis on the comparison between TPE and alternative approaches, the assessment of performance metrics, including loss curves, confusion matrix and consistency among precision, recall, and F1-score, the interpretability of real-time results and computational feasibility analysis, and the investigation of the system's operational resilience in the presence of delays, communication failures, and conflicting decisions between human operators and the AI system.

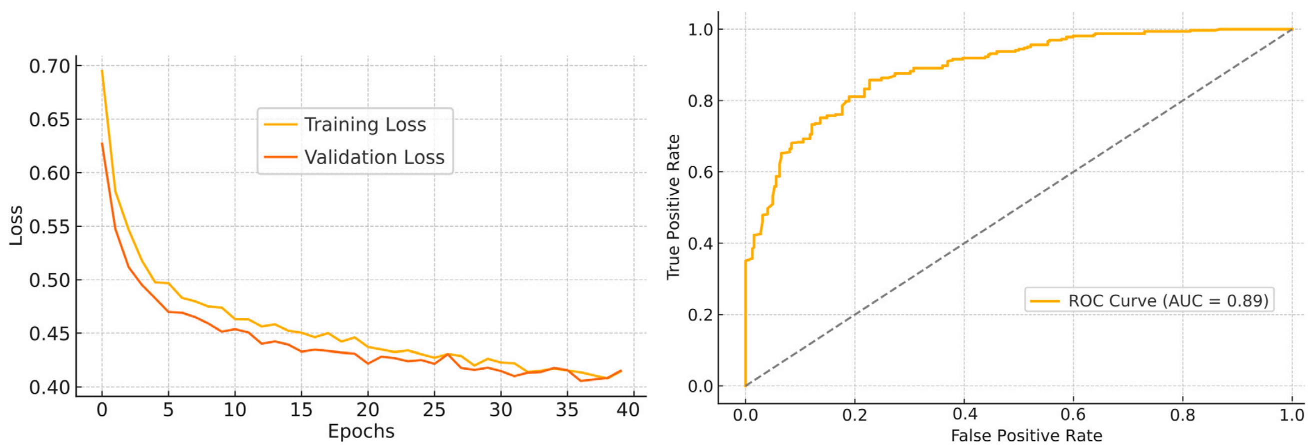
4.10.1. Hyperparameter optimization strategies

During the experiments, different hyperparameter optimization strategies were evaluated to enhance the performance of the model in classifying operational events. The grid search method was initially tested, but proved impractical due to its high computational cost and limited ability to explore high-dimensional search spaces. Subsequently, a generic Bayesian optimization strategy was applied, yielding accuracy levels similar to those of the TPE. However, it required more iterations to converge, resulting in a longer total execution time. Given these limitations, the TPE was selected as its efficiency in navigating promising regions of the search space accelerated the tuning process and produced a more stable final configuration.

The probabilistic acquisition function of the TPE played a key role in reducing the number of evaluations and improving performance at a lower computational cost, allowing multiple tuning rounds without compromising overall execution time. Beyond statistical improvements, the use of TPE contributed to practical gains in the detection of operational errors. The final combination of hyperparameters improved the model's sensitivity to topological and temporal variations in recorded events, directly reducing the incidence of false negatives. This improvement is evident in the confusion matrix and in class-specific metrics such as precision, recall, and F1-score, indicating that the optimization process not only increased the overall accuracy, but also refined the discriminative capacity of the model under real operational conditions.

Table 12
Comparison between traditional protocols and the proposed AI-based automated protocol.

Criterion	Traditional protocols	Automated protocol with AI
Maneuver execution	Manual sequence, prone to errors	Automated sequence with real-time validation
Documentation	Post-execution generation, often fragmented and unstructured	Automatically generated and standardized during execution
Interlocking validation	Fixed rules or reliance on experts	Dynamic interlocking with multi-topology verification
Fault detection	Visual inspection or post-event log analysis	Automated classification by RCNN with initial accuracy of 82.9%
Traceability	Limited to local files and dispersed records	Consolidated in databases with audit trails
Adaptability	Limited adaptability to new topological scenarios	Generalization validated in three substations with multiple agents
Response time	Dependent on operator experience	42.7% reduction in average response time



(a) (b)

Fig. 14. Performance metrics and training evaluation: (a) loss function trajectory during training and validation and (b) ROC curve with AUC value for the optimized RCNN model.

4.10.2. Performance metrics and evaluation

The performance of the optimized RCNN model was assessed using quantitative metrics that reflect its learning ability, generalization, and discriminative power. Fig. 14(a) displays the trajectory of the loss function over 40 epochs for the training and validation sets. A steady and progressive convergence was observed, with no abrupt fluctuations or significant divergence between the curves, indicating a consistent learning process and the absence of overfitting. Fig. 14(b) presents the AUC-ROC curve derived from the continuous scores generated during the testing phase. The area under the ROC curve reached 0.89, suggesting strong model capability in distinguishing between correct and incorrect operational sequences. The steep initial slope and proximity of the curve to the upper left corner further emphasize the sensitivity of the classifier, even under conditions of class imbalance (see Fig. 14).

Complementarily, the confusion matrix in Fig. 12(a), along with the results presented in Tables 8 and 9, confirmed the stability of the model in balancing precision and recall. The distribution highlights the model's tendency to minimize false positives, aligning with operational safety requirements. The F1-score for the error class reached 78.6%, a value consistent with applications in critical contexts. Together, these indicators reinforce the feasibility of the proposed solution, demonstrating consistent and reliable performance in time-constrained environments with stringent fault detection demands.

4.10.3. Interpretability and performance constraints in real-time environments

Interpretation of the RCNN model was not performed using techniques such as SHAP or attention mechanisms due to the dual structure of the architecture, which integrates textual sequences with numerical variables. The mixed dimensionality, combined with the use of overlapping sliding windows, limited the direct applicability of standard interpretability tools. As an alternative, an indirect validation was performed that evaluated the consistency of the predictions with predefined rule sets and expected semantic distributions, ensuring alignment between the generated scores and previously established failure patterns. Regarding false negatives, the model correctly identified 262 faulty events but did not classify 60 cases, resulting in a false negative rate of approximately 18.6%. In real-world applications, such omissions may compromise operational safety.

To reduce this risk, two complementary strategies were implemented. The first involved activating dynamic blocking mechanisms programmed to operate based on logical rules stored in the database BD_4, even in the absence of a positive classification by the model. The second consisted of integrating audit trails into the database BD_6, enabling manual review in real time of events deemed critical. The average response time of the automated protocol was approximately 1.03 s per sequence, including the data retrieval, vectorization, inference, and blocking stages. This value was compared to the average response time of manual routines observed in three substations, which was 1.80 s per operational decision. The reduction 42.7% was statistically significant, with a p-value < 0.01 in a paired two-tailed t test using 40 matched operations per protocol.

Finally, the system's computational requirements were assessed by executing the model in a realistic operational environment. The simulation and computational experiments were conducted on a notebook equipped with an Intel(R) Core(TM) i7-7700HQ processor (2.80 GHz, 4 cores, 8 threads), 32 GB of RAM and an SSD. The system featured two GPUs: an NVIDIA(R) GeForce GTX 950M with 2 GB of dedicated memory and an integrated Intel(R) HD Graphics unit. The operating environment was Windows 10 Pro 64-bit, version 10.0, build 19045, running DirectX 12. Despite being a legacy configuration, it supported the efficient execution of deep learning models and optimization routines. During inference, the computational load remained below 12% of the CPU capacity and did not exceed 1.5 s, even when five instances were executed in parallel. In addition, communication between databases BD_1 and BD_6 was handled by a local bus with a latency below 80 ms. These results confirmed the feasibility of real-time execution in transmission networks with multiple agents and a standardized computational infrastructure.

4.10.4. Operational robustness and conflict handling

The implementation of the automated protocol in a simulated environment enabled assessing its resilience to communication failures and state reading delays. During testing, artificial delays were introduced in the signals from the database BD_2, which stores the status of the real-time equipment. In these scenarios, the system operated in a temporary tolerance mode, retaining the last known state for up to 2.5 s before triggering a preventive sequence block. This tolerance window was calibrated to ensure operational continuity without compromising safety. In cases of complete communication loss with databases BD_1, BD_2, or BD_4, the protocol automatically stopped the execution of the maneuver, issued an alert via BD_6, and logged the inconsistency in the audit record.

Interlocking logic conflicts were also addressed. The simulation scenarios included simultaneous requests from two operators that targeted the same circuit breaker. The system resolved such conflicts based on the timestamp of the request recorded in the database BD_3, combined with the operator's priority level, as defined by the rules stored in BD_4. When two requests were received within the same 100 ms interval, the protocol required explicit confirmation from the higher priority operator and blocked the execution of the second request until resolution. This mechanism effectively prevented operational conflicts while respecting the hierarchy established by the dispatch control centers.

Regarding the possibility of overriding AI decisions, the system was designed to accept human intervention at any stage of the maneuver. When an operator contested the automatic classification of an event, a new label could be manually entered through the supervision interface. This entry was immediately recorded in the database BD_5, along with the reason for the override, the operator's credentials, and the time stamp of the decision. This functionality ensured full auditability of human interventions and allowed supervised use of the AI system, particularly in complex or novel scenarios where human judgment remained essential.

5. Discussion

This study proposed an automated protocol for operational maneuver control in electrical substations, integrating sequential logic, document generation, and event classification through RCNN. The approach addresses the limitations of traditional systems, such as the lack of continuous validation, the dependence on manual forms, and the challenges in coordination among transmission agents. By modeling events stored in operational databases and incorporating AI, the protocol aimed to improve safety, standardization, and decision-making autonomy in supervised operational environments.

The protocol was applied in five case studies involving transmission lines, busbars, and 525 kV transformers, demonstrating operational feasibility and measurable gains. The system reduced maneuver preparation time to approximately 30 min, with automatic report generation, traceability through a segmented database, and real-time decision support. The AI model achieved an accuracy of 82.92% in classifying operational events, allowing early identification of errors and adaptation to the topologies analyzed. These results suggest that the proposed solution enhances reliability, responsiveness, and auditability in clearance and normalization processes within shared substations.

5.1. Integration of spatial–temporal features and model resilience

The AI model developed in this study incorporated an RCNN architecture designed to coordinate the spatial and temporal attributes embedded in the operational substation records. The convolutional layers extracted structural patterns from textual descriptions and equipment states, while the recurrent layers, implemented with GRU units, modeled the chronological sequence of maneuvers. This integration enabled the identification of causal relationships between successive events, capturing both the local context of each operation and the temporal progression of the process. To ensure temporal coherence between records, a sliding-window mechanism was used to group consecutive events into contextual blocks. This structure facilitated the detection of operational failures related to incorrect command sequencing, redundant actions, and missing steps. Unlike approaches that treat events in isolation, the sequential modeling adopted in this study reflected the logical flow of maneuvers, thus reducing the need for manual intervention and improving the reliability of the decision support system (Mohammadi et al., 2024).

The resilience of the architecture was evaluated through ablation experiments, in which specific components of the RCNN were selectively disabled to measure their impact on the accuracy of classification. Removing the convolutional layers impaired the ability to detect local structures, while excluding the recurrent layers compromised the sensitivity to temporal patterns. These modifications resulted in accuracy losses of up to 18.4%, confirming the importance of hybrid architectural design (Gregory et al., 2018). Regarding model security, sanitization routines were implemented during preprocessing to remove inconsistent, duplicated, or critically incomplete events. In addition, heuristic rules were applied to perform semantic validation of textual descriptions, preventing the propagation of artificial noise or malformed inputs in the analyzed windows. These measures increased the reliability of the inferences and reduced the model's vulnerability to adversarial attacks involving input manipulation (Rubinstein and da Vinha, 2018).

5.2. Applicability of the protocol and current limitations

The results of this study reinforce the evidence in the literature on the potential of RCNN to classify operational events in substations. Machine learning techniques have been successfully applied to the identification of failures and critical patterns, particularly in contexts involving high-density data from large-scale measurement systems and smart grids (A. et al., 2023; Gregory et al., 2018; Miraftabzadeh et al., 2021; Jian et al., 2020). In the present work, although the available dataset was limited in size, the model effectively identified irregular events and supported operational decisions, suggesting that expanding the dataset is likely to further improve performance.

The adopted approach aligns with recent trends in the modernization of the power system, which emphasize the automation of operational analysis and intelligent document generation. Similar techniques have shown promising results in load forecasting (Fatima et al., 2024), power quality disturbance detection, and cybersecurity (Rubinstein and da Vinha, 2018; Alimi et al., 2020; Song, 2021). In this context, the proposed protocol also incorporated automated mechanisms for document generation, reducing inconsistencies and accelerating information exchange among agents. In addition to contributing to system resilience, this strategy helped preserve data privacy by avoiding manual retransmission of sensitive information (Azizi et al., 2024).

However, in previously unrecorded cases, operations not covered by historical data, the model encountered limitations related to the completeness of automatically generated information. As a mitigation measure, the system required the operator to perform a final review prior to executing the maneuvers, allowing the inclusion of unstructured instructions or additional data through the graphical interface. This manual step ensured the integrity of the documents issued under exceptional conditions, although full automation remains dependent on the future consolidation of a structured *ad hoc* instruction library. Thus, the solution combined automatic standardization with supervised human validation, balancing operational safety and flexibility.

Furthermore, common obstacles to substation digitalization – such as compatibility with legacy systems and protocol heterogeneity across utility companies – were taken into account during the development of the protocol. The model was designed to operate in parallel with SCADA environments, employing modular databases and interfaces adaptable to different operating architectures. This approach enabled progressive integration with existing systems without requiring physical modifications or equipment replacement, thus extending its applicability even in hybrid infrastructures or under regulatory constraints (Sadeghi and Kalantar, 2023; Arthur et al., 2020; Grottum et al., 2019; Shah et al., 2024).

5.3. Cost, accessibility and implementation feasibility

The investigation identified that most transmission companies still relied on conventional approaches for recording and executing maneuvers, often using manually filled `.xlsx` spreadsheets (Kulkarni et al., 2021). Some utilities used expert systems with proprietary databases, allowing procedural adjustments based on accumulated operational experience. Others, with more advanced technological maturity, implemented automated maneuver generation models based on formal structures such as graphs and Petri nets (Oikonomou et al., 2021). However, these solutions frequently required manual intervention and were not compatible with various substation topologies, affecting standardization and operational continuity.

Despite the advancements introduced by these innovations, expert systems face significant limitations related to maintenance, adaptability to heterogeneous operational environments, and licensing costs (Chaves et al., 2022; Dandea and Grigoras, 2023; Hengxuan et al., 2019). In many cases, automation modules operated in parallel with supervisory systems and required frequent updates, hindering their consolidation as permanent solutions. These limitations directly affected maneuver efficiency, with preparation times often exceeding two hours per operation, particularly in scenarios involving multiple agents (Vladimirovich Borodin et al., 2020).

The proposed protocol significantly reduced the preparation time by automating document generation and communication with involved agents. In the tests conducted, the total time from the beginning of the analysis to the submission of the procedure for the final review was under five minutes. With manual verification and data review, the complete preparation of the maneuver was completed in up to 30 min, even in scenarios involving multiple permissions and sequential steps. Achieving this performance required addressing technical challenges related to sequential event modeling and the consolidation of integrated databases, which were overcome using low-cost and highly adaptable computational solutions. However, preliminary tests indicated resistance from operators accustomed to conventional routines, highlighting a common barrier to the adoption of automated solutions (O'Connor et al., 2019; Hocking et al., 2023).

Regarding solution accessibility, the pilot implementation required only the existing substation hardware (standard operating computers and local network connections), along with a software package developed in Python using open source libraries. Cost estimates indicated that the investment required for the complete implementation of the protocol in a typical substation was approximately 35% lower than the average cost of expanding dedicated modules in commercial SCADA systems. The absence of proprietary licensing requirements, combined with interoperability with legacy systems, facilitates adoption in real operational settings, as demonstrated in the pilot application.

The estimates were based on average proportions derived from typical SCADA system deployments. In medium-scale industrial projects, costs related to licensing, integration, and engineering services generally account for approximately: 30% of the total for the core SCADA license, 10% for tag-based extensions, 15% for integration with programmable logic controllers and standardized communication interfaces (OPC drivers), 15% for annual maintenance during the initial phase, and 30% for implementation and commissioning. Based on these proportions, the proposed protocol, developed using open source software and leveraging existing infrastructure, required an investment approximately 35% lower than the average cost of expanding dedicated modules in commercial SCADA environments.

5.4. Remaining gaps and future directions

One of the main challenges encountered during the study was the definition of an appropriate decision threshold to classify operational events. Balancing sensitivity and specificity required fine-tuning of the neural network hyperparameters to minimize false positives and the omission of relevant events. Furthermore, the training process demanded substantial computational resources, particularly for optimizing the sliding windows used to preserve the temporal coherence of the data. The limited volume of available records imposed further constraints, requiring careful modeling of the temporal patterns embedded in the maneuver sequences.

Despite the advances achieved, important operational gaps remained, particularly in terms of complete integration between automatically generated documentation and procedures that are effectively executed in real environments. Although the protocol automated the generation of reports and maneuver instructions, the execution of these steps still relied on manual validation and operator confirmation. This separation between the documentation and action layers reflects a recurring issue in control systems, as also reported in the literature by Biswas and Centeno (Biswas and Centeno, 2022), who emphasized the challenges in formulating operational sequences that effectively bridge planning and execution under dynamic and topological constraints. Moreover, the current model did not autonomously identify or classify the specific types of error associated with each maneuver. This limitation reduced the system's ability to provide interpretable diagnostics to operators, which is essential for applications in high-criticality environments. Furthermore, adaptive routines for real-time adjustment of the decision threshold were not implemented, partially limited the adaptability of the model to different substation configurations and operational conditions.

For future directions, the development of attention mechanisms is recommended to highlight the most relevant patterns in event time series. Although such integration could improve model interpretability, it was not implemented in the present study due to the architectural modifications and validation procedures it would require. Conceptually, attention-based approaches, such as self-attention layers or transformer variants, can assign contextual weights to event sequences, emphasizing critical transitions and irregularities. However, in operational environments characterized by limited annotated data and the need for lightweight and interpretable models, adopting these techniques involves careful trade-off considerations.

In this study, interpretability was ensured through heuristic routines, ablation experiments, and semantic input structure, which were sufficient for the targeted operational context. Future improvements may involve dynamic decision calibrators based on online performance metrics and the direct integration of document generation modules with automated execution through reliable orchestration protocols. In addition, training of new models is proposed using enriched labels that can automatically distinguish between sequence errors, redundant actions, and permission gaps, to consolidate the solution as an autonomous and reliable tool for substation operations.

5.5. Scientific contribution and implications

This study presents an original scientific contribution by proposing an automated control model for operational maneuvers in substations, integrating event classification, document generation, and coordination between agents in the power sector. The proposed solution addresses a methodological gap that remains underexplored in the literature: the lack of mechanisms that combine AI, logical event sequencing, and intercompany authorization protocols. By articulating these components within a unified architecture, the work advances toward transforming fragmented operations into coherent, auditable, and traceable processes, supported by structured operational databases. This approach aligns with emerging guidelines for modernizing the power sector, which call for interoperable, autonomous, and secure solutions to manage critical systems (Ravandi et al., 2024).

The practical applicability of the solution was validated through case studies using real substation data, including scenarios involving transmission lines, busbars, and 525 kV transformers. The model significantly reduced maneuver preparation time, eliminated recurrent documentation errors, and supported operators' decision making through automated classifications. Unlike classical approaches that rely on symbolic logic, complex graphs, or Petri nets, the proposed solution operated with accessible computational resources and remained compatible with the systems currently used in medium- and large-scale substations.

Additionally, the proposed approach demonstrated generalization potential through a modular structure that allowed adaptation to different topological and operational configurations. The automatic identification of deenergized equipment based on circuit breaker states, along with the model's flexibility to handle variations in authorization protocols, reinforced its applicability in diverse contexts. For these reasons, the developed protocol not only delivered immediate operational benefits, but also established a solid foundation for advancing autonomous and interoperable solutions in the power sector, in alignment with the critical infrastructure digitalization guidelines.

6. Conclusion

The approach presented in this study consolidates a methodological innovation by integrating, within a single automated protocol, the sequential analysis of operational events, the structured generation of documentation and the execution of maneuvers in electrical substations. It constitutes an original scientific contribution by proposing an architecture that combines AI with operational logic, promoting procedural standardization, interoperability among sector agents, and optimization of operational management. This approach addresses the increasing complexity of power system operations by offering solutions that reduce errors and improve safety through automated control and documentation.

Thus, the main hypothesis was confirmed and all specific objectives were fully achieved, with measurable gains in efficiency, autonomy, and consistency in maneuver management. The solution demonstrated practical applicability in real-world scenarios, with a direct impact on reducing operational inconsistencies, response time, and improving traceability. In addition, its modular design and independence from proprietary technologies confer a high generalization potential, supporting its progressive adoption across diverse topological and institutional configurations. Therefore, this work provides a concrete foundation for the transition from fragmented systems to more intelligent, auditable, and resilient operational environments.

The results indicate that the system contributes to maneuver standardization and fault reduction, thereby enhancing operational safety and efficiency. The simulation interface proved to be a promising tool by enabling intuitive execution and documentation of maneuvers in compliance with regulatory requirements. The AI methodology introduces an innovative approach that uses sliding windows to extract temporal patterns, improving the sequential analysis of operations. Therefore, the proposed solution demonstrates significant potential for modernizing maneuver management in electrical substations, fostering greater reliability and safety in the sector.

CRediT authorship contribution statement

Gustavo Havila F. Campos: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Viviane M. Gomes Pacheco:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology. **Marcio Rodrigues C. Reis:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology. **Clóves Gonçalves Rodrigues:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology. **Saulo Rodrigues Silva:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology. **Antonio Paulo Coimbra:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation. **Wesley Pacheco Calixto:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no financial interests or conflicts of interest that could compromise the objectivity, integrity, or impartiality of this research. No external funding, patents, or financial compensation were received for this work.

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Data availability

Data will be made available on request.

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