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Advancing Electrical Losses Assessment Methods in Power Systems

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ABSTRACT

The operation of modern power systems requires a sophisticated technological infrastructure to effectively manage and evaluate their parameters and performance. This infrastructure includes the generation, transmission and distribution power system components. This paper provides an overview of the loss evaluation to a part of Kosovo's power system, substation with wind and photovoltaic (PV) energy sources integrated (SS Mramori, SS Kitka, and SS Kamenica) and the analysis of the loss assessment methods. One the assessment method in the research encompass simulated loss scenarios and their corresponding values in network components, employing the simulation based on the respective software tools. In current trends, power systems are visualized through the Supervisory Control and Data Acquisition (SCADA) platform. However, in Kosovo, although losses are integral to the SCADA system, they are represented as a overall value in the online mode, not encompassed depict losses per-components in real-time. This limitation hinders effective online power system optimization regarding the losses. As consequence, the purpose of this study is proposal a logical method developed through neural networks. The methodology incorporates various parameters, including as inputs variables; voltages, currents, active and reactive powers, and their computed values for extracting losses ($X(x_1, x_2, ..., x_n)$). These parameters undergo systematic processing through hidden layers ($Y(x_1, x_2, ..., x_n)$), leading to the classification of components within the power system. Finally, at the output stage ($A(x_1, x_2, ..., x_n)$), an assessment is conducted based on the level of losses observed in the components of the power system. This implementation method promises significant benefits for transmission systems, impacting not only reducing losses, power quality but also yielding economic advantages.

Keywords: electrical losses, power systems, SCADA, neural network, classification, assessment, monitoring.

INTRODUCTION

Estimating losses in a power system is a crucial factor for attaining optimal performance, influencing both system management and optimization. Additionally, it plays a pivotal role in the economic costs.

The efficiency analysis of power system, optimization, enhancement of power quality, and minimization of economic costs inevitably also includes the evaluation of losses (Zheng and Shahabi, 2023; Elahi et al., 2023). The modernization and meticulous design of these networks are imperative for sustaining optimal operational performance, with a particular focus on power electrical losses. In recent years, significant advancements in the evaluation methods of power systems have materialized through the integration of smart tools and comprehensive Supervisory Control and Data Acquisition (SCADA) systems, enabling real-time monitoring of network components (Garip et al., 2022; Rexhepi, 2023).

In the realm of power system problem-solving, traditional methods like practical numerical optimization techniques such as lambda iteration and Newton–Rapson methods have been conventionally applied. However, as optimization problems in power systems tend to be inherently nonlinear and, with the inclusion of diverse constraints, become slow and intricate, there is a growing inclination towards employing artificial intelligence (AI) techniques (Pandey et al., 2023). The process of determining the type of neural network, the optimal number of layers, and the appropriate number of neurons in each layer is typically conducted through a trial and error approach. This method involves analyzing various factors, including the number of neurons, linear regression of the involved variables, and the maximum allowable error (Laurencio-Pérez et al., 2022). Artificial neural networks offer numerous advantages, including distributed information storage, the integration of information processing and storage operations, autonomous planning of information processing, self-learning capabilities, and inherent fault tolerance and robustness. Leveraging these strengths, artificial neural networks have found widespread applications across diverse fields. They have been successfully employed in automatic control systems, composition optimization tasks, pattern analysis, graphics processing, robot control, and various medical applications. The versatility of artificial neural networks makes them a powerful and adaptable tool for addressing complex challenges in a range of domains (Su Dai et al., 2022).

The absence of online loss assessment in various components of Kosovo's power transmission system, including components like transmission lines, transformers, interconnecting lines with neighboring countries, as well as generation and distribution systems, represents a significant shortcoming in conducting thorough real-time evaluations and monitoring of losses. This deficiency serves as the basis of this research, aiming to propose advancements in intelligent methods/neural networks and their integration within SCADA management systems. This integration would bring added value to online loss assessment and monitoring capabilities for operators in the Transmission Systems Control Center. Such enhancements are the potential ways to optimize the online system, enhance its performance, and simultaneously yield positive effects on economic costs, with a constant focus on reducing and control the electrical losses.

Background

The accurate and reliable determination of the parameters in operating mode constitutes the fundamental groundwork for tackling issues related to the analysis of energy efficiency (EE) losses. It serves as the basis for devising organizational and technical measures to enhance effective management and establishing the benchmark for energy efficiency losses (Muratov et al., 2021). The analysis of losses also incorporates the k-Means clustering method, a highly efficient distance-based clustering algorithm. To further enhance efficiency evaluation, principal component analysis (PCA) is employed as a pre-processing step. PCA selectively extracts and interpolates losses feature data from the network components, contributing to a more refined evaluation process (Ma et al., 2019; Ymeri et al., 2023).

The neural network prognosis algorithm (NNPA) stands out as a straightforward method for conducting the loss calculations. This technique relies on technical parameters obtained through a load flow analysis based on Newton-Raphson, considering operational parameters. Within dense layers, the algorithm processes these parameters, leading to the determination of output parameters. For instance, in the case of wind turbines, factors such as temperature, wind speed, and precipitation are taken into account. Similarly, in photovoltaic (PV) systems, the algorithm considers parameters like solar radiation, humidity, and temperature. The data is efficiently processed and calculated using the forecasting algorithm, resulting in accurate outcomes with minimal computational steps (Shariq et al., 2023).

Neural network (NN) models are also applied in the distribution network to achieve other results, considering unplanned power outages and seeing future predictions of the system state (Sayar and Yüksel, 2020).

The intricate infrastructure overseeing the generation, transmission, and distribution of power system is inherently reliant upon extensive and complex datasets. Supervisory Control and Data Acquisition (SCADA) are dedicated to managing and monitoring power systems encompass tasks such as monitoring, execution, data processing, handling component failures, and addressing various energy parameters (Otcenasova et al., 2019). The monitoring and calculation of power losses emerge as a important consideration, particularly from optimization and economic cost perspective (Cinar, and Kaygusuz, 2020; Albogamy et al., 2022; Rexhepi and Hulaj, 2020). The integration of renewable resources into power systems further increase the data processing complexity within SCADA (Tautz-Weinert and Watson, 2016; Tao, 2021), introducing challenges related to real-time integration and loss calculation (Lu Shen et al., 2019). Real-time monitoring methods and analysis for power losses in electrical transmission and distribution systems constitute the most efficient means of assessing and optimizing loss (Moldoveanu, 2019).

The existing literature by various authors explores the assessment of losses and the diverse methods employed in power systems. The discourse within this body of literature comprehensively scrutinizes the analysis of losses across transmission electric power systems, distribution systems, and renewable sources. These losses are evaluated through various methodologies, encompassing intelligent methods, neural networks, SCADA systems, and simulation techniques utilizing different software applications. Despite the breadth of research, a notable gap persists in the development of precise loss estimation methods aligned with the classification and categorization of losses within power systems in real time. This gap prompts the need for further advancements in assessment techniques. Accordingly, the aim of this study is to contribute to this advancement by leveraging neural networks for the classification and categorization of losses to all the components of power systems in real time, respectively transmission power system.

MATERIALS AND METHODS

Study area

The scope of this study encompasses a part of the power transmission system, specifically focusing on the eastern part of the 110 KV Transmission System Operator. This area includes several substations, namely SS Pristina 4 (20/10 kV), SS Ferizaj 1 (110 kV), SS Gjilani (110 kV), SS Gjilani 5 (110 kV), SS Berivojca (110 kV), SS Vitia (110 kV), SS Sharri (110 kV), and SS Bujanovci (110 kV). Additionally, the analysis incorporates three substations: SS Ktika (110 kV) dedicated to wind systems, and two substations, SS Mramori (wind parks) and SS Kamenica (photovoltaic and wind parks), which are planned for integration to the Transmission System Operator.

Research materials

This paper employs two types methods with the aim of classifying and categorizing losses in the power system. The first method involves simulations considering data from substations, busbars, lines, transformers, cables, and power generation sources (wind and PV systems), as well as load-related parameters (ractive and eactive power, curents, voltages, impedances). These parameters are incorporated into their respective models using the software package (ETAP, 2023). The second method involves the building of a model using neural networks, which includes an input block, a parameter processing block, and an output block for presenting the results.

Methods

The methods employed to attain the research objectives have been designed to ensure the extraction of highly reliable results. This approach is aimed at constructing robust ideas and fulfilling the research's primary purpose, which involves proposing a classification and evaluation system for losses in the electric power system.

The methodologies employed in power transmission systems encompass key components, including substations, power lines, transformers, and considerations related to electricity generation and load management. The Kosovo Transmission System has implemented the SCADA platform within substations and the central control room (Dispatch Center). This platform processes and displays data, including power, load, voltages, and currents, for components like; lines, transformers, energy sources, and loads, representing an advanced approach to system management and monitoring. However, a limitation exists in the current practice, where losses are aggregated into a single total value for all components.

To address this shortcoming, a part of the system has been modeled for result extraction through simulations. The inclusion of wind and photovoltaic generation in these simulations provides a more realistic overview, contributing to a comprehensive understanding of the problem and the fulfillment of research goals. The simulation method served as a valuable basis, enabling comparisons and as reference to other advanced methods, notably neural netowrk approaches. The data processing methodology involved the utilization of diverse models characterized by component parameters such as active (P) and reactive (Q) power, voltages (V), currents (I), and impedances (Z). Subsequent to this, a series of calculations and scenarios are implemented to interpret and analyze operational results. In the paper are introduced a fundamental architecture illustrating loss modeling methods in a broader comparative and integrative context. Figure 1 delineates a hierarchical structure showcasing the processing of component data, methodologies for the assessment of electrical losses, and the interconnection and transmission of data between local and central power system centers. This approach promises a more reliable and advanced optimization of the Kosovo Transmission System in the loss assessment and monitoring.

One of the models utilized for loss assessment incorporates the use of software platforms. These platforms enable the modeling and simulation of the diverse components within the electrical power system, as illustrated in Figure 2.

The model encompasses a part of the transmission power system operating at the 110 kV level, with three identified swing nodes (SS Prishtina 4 220/110 kV, SS Ferizaj 2 110 kV, and SS Berivojca 110 kV). The other nodes represent the integration of wind and PV sources in substations SS Mramori, SS Kamenica, and SS Kitka (installed power capacity of approximately 200 MW). The active and reactive power fluxes are designed using the Newton Raphson method to calculate the losses. The methods implemented through simulations, not only provide insights into recognizing losses within power system components but also elucidate their effects on the voltage profile (Figure 2).

In addition to the methodology involving simulation models through software, neural networks

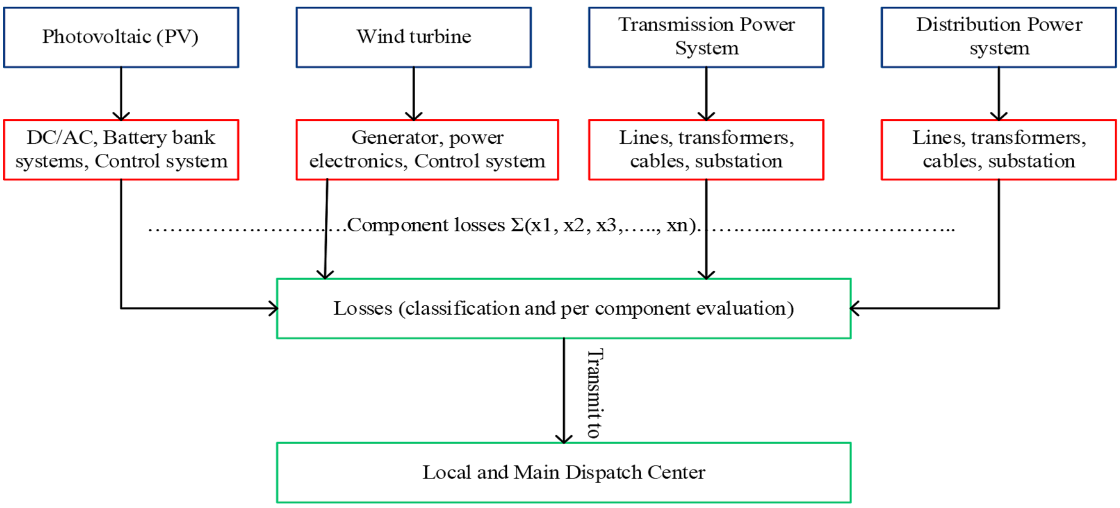

Figure 1. A comprehensive overview of the hierarchical framework for classifying and categorizing losses

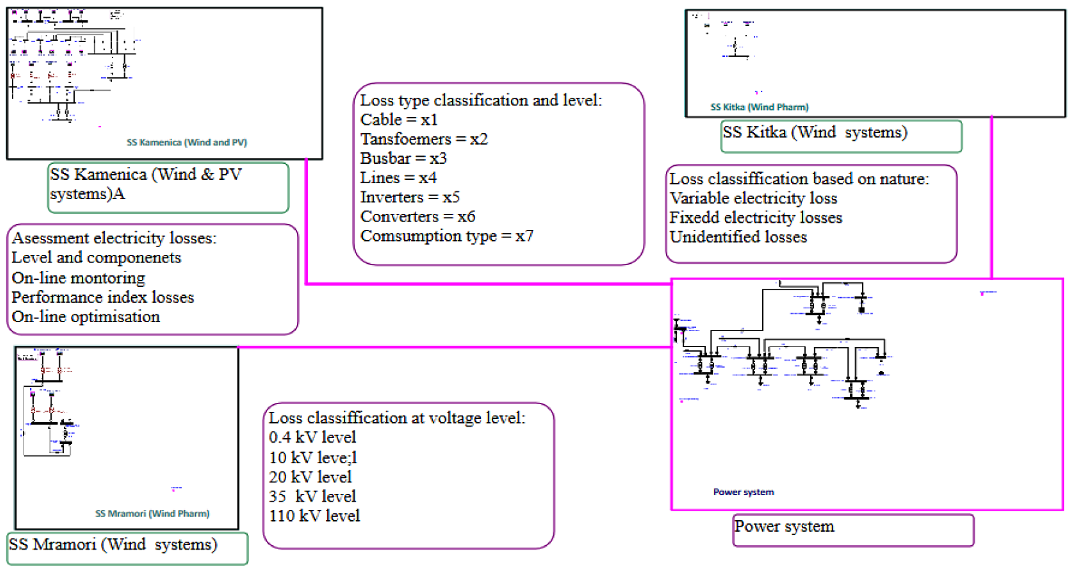

Figure 2. The power system modeling for the analysis of power losses

stand out as an exceptionally advanced approach. This sophisticated tool entails an evaluation process, beginning with input parameters, followed by the comprehensive training of the neural network, ultimately leading to the attainment of desired results.

In the following, is utilized models based on neural network systems for classifying losses. The input data for the proposed NN model include the initial voltage magnitude, the sum of active power injection, and reactive power injection for each bus. The output data for training will be steady-state voltage magnitude for each bus and active power flow for each branch (Pham and Li, 2022).

Intelligent and artificial methods signify a sophisticated technological approach with promising capabilities for result analysis. In the realm of loss monitoring and classification, the neural network method is employed. This method is constructed with an input block, data processing through hidden layers, and an output block that yields results based on the input information and queries. The fundamental expressions describing such a model are outlined as follows:

$$y = \sigma(w^T x + b) \tag{1}$$

$$z = w^T z + b = w_1 x_1 + ... + w_d x_d + b \tag{2}$$

In this context, a linear equation is expressed as a combination of features or predictors denoted by (d), where $a = \sigma(Z)$ is represents the activation function, introducing the non-linear aspect to the Neural Network for refined predictions (y). The notations are elucidated as follows:
$x = (x_1, ..., x_d)^T \in K_d$, represent a vector comprising (d) features/predictors, the weight vector $w = (w_1, ..., w_d)^T$ – is associated with the features (x), b – is referred the bias. The observation from (m) training samples denoted by $\{(x^{(1)}, y^{(1)}), ..., (x^{(m)}, y^{(m)})\}$ (Grohs and Kutyniok, 2022). The Equation (3) for the neural network model can be extended as an matrix form:

$$A = f(WX + B) \tag{3}$$

In the Equation 3, A is the activation matrix, each column represents the activiation of a neuron, f is the activation function, W – weight matrix, X – input matrix (each column represent an input feature vector), and B – Bias Matrix. After the parameters processing, during training, the network's predictions are compared to the aim target using a loss function, and the network's parameters (weights and biases) are adjusted through backpropagation and optimization algorithms to improve performance. In classification tasks, it is common to use a softmax function in the output layer to convert the raw activations into probabilities. The softmax function takes the output of the neural network (the activations of the output layer neurons) and transforms them into a probability distribution over multiple classis. This is particularly useful for multi-class classification problems.

$$softmax(ai) = \exp\,(ai/\textstyle\sum(\exp(aj)) \tag{4}$$

where: ai – is the activation of output neuron i,
aj – is the activation of output neuron j,
$softmax(ai)$ – is the probability for class i (Akhtar et al., 2023; Yathish, 2022).

This research paper explores the integration of diverse methodologies, encompassing simulation techniques, intelligent methods, and neural network approaches, with the goal of enhancing the operational performance of energy systems. The paper introduces developed approaches and proposes a method for the classification and categorization of losses. The primary objective is to classify and categorize loss values across all components, including transmission networks, and explore the potential integration of losses into the SCADA system for processing all main components. Additionally, the paper provides an opportunity for a comparative analysis of the methods employed, consistently highlighting their roles in improving the efficiency and accuracy of loss assessment. This comprehensive and integrative analysis is visually presented in Figure 3.

RESULTS

In the model depicted in Figure 2, the results highlight the levels of losses, their evaluation, effects on voltage profiles across various nodes within the simulated power system. Figure 4 provides an overview of the impact on voltage profiles when integrating wind turbines and photovoltaics in the respective substations.

An examination of losses in the 110 kV transmission lines, interconnecting various components of the modeled system, is presented in Figure 5, respectively (a, b, c) to the 110 kV L 2-2 line, connecting SS Kamenica and SS Gjilani 5, exhibits a substantial percentage of losses despite being loaded, according to the models.

An examination of losses in the 110 kV transmission lines, interconnecting various

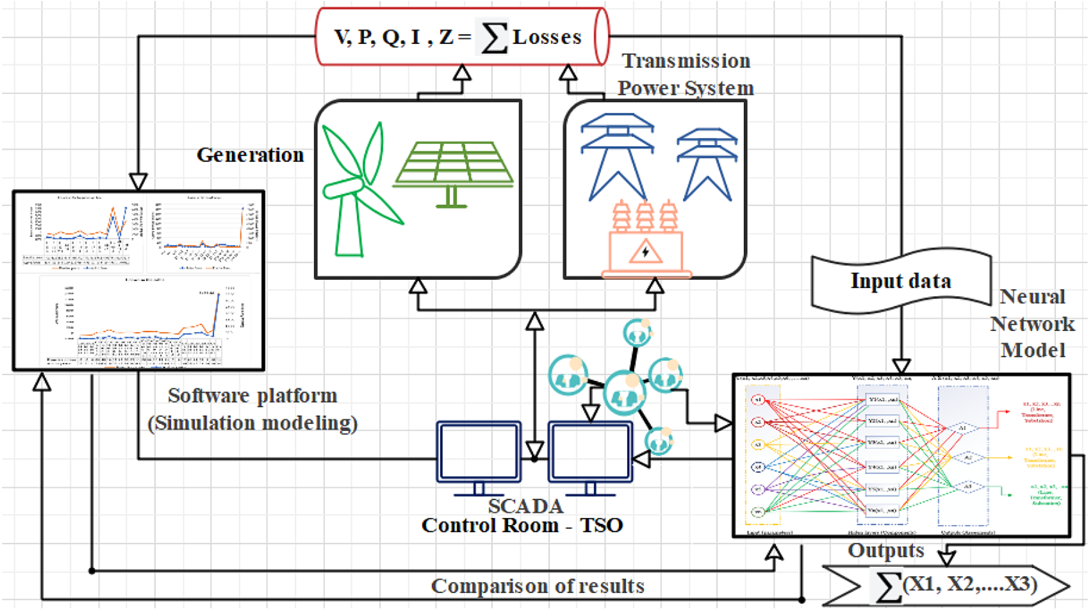

Figure 3. The integration of various methodologies employed for the estimation of losses within the power system

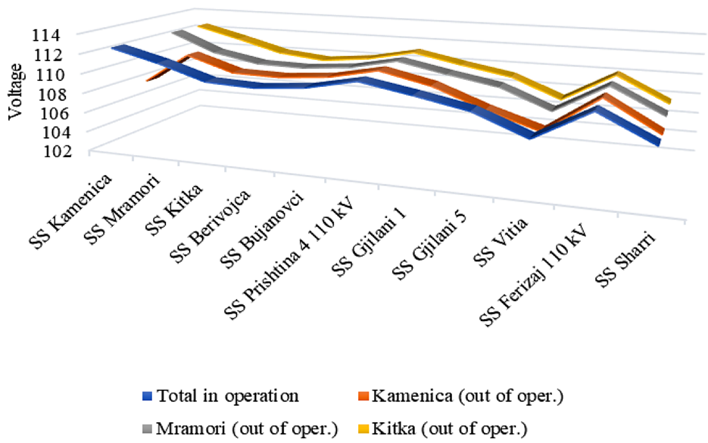

Figure 4. Voltage profile performance

components of the modeled system, is presented in Figure 5a, to the 110 kV L 2-2 line, connecting SS Kamenica and SS Gjilani 5, exhibits a substantial percentage of losses despite being loaded, according to the models. Figure 5b presents an analysis of electrical losses in power transformers, offering insights into various characteristics and the influencing variables. Notably, the losses in the distribution system become more pronounced at the 0.4 kV and 10 kV levels, particularly in substations with concentrated wind and photovoltaic production, as indicated by the results. The analysis extends to encompass both active and reactive power losses in the cables connecting the wind and photovoltaic (PV) systems to substations at both the distribution system's 10 kV and 0.4 kV levels. The results reveal a distinct pattern wherein substations with a higher concentration of photovoltaic (PV) systems experience more substantial losses (Figure 5c).

The simulation platform and its outcomes emphasize the essential role of these methods in research. Beyond being mere advanced tools, they offer comprehensive insights by visually depicting the components of power systems. The assessment is carried out considering the presentation level and degree of detail of these components. However, it is crucial to acknowledge the complexity associated with constructing models and inputting data.

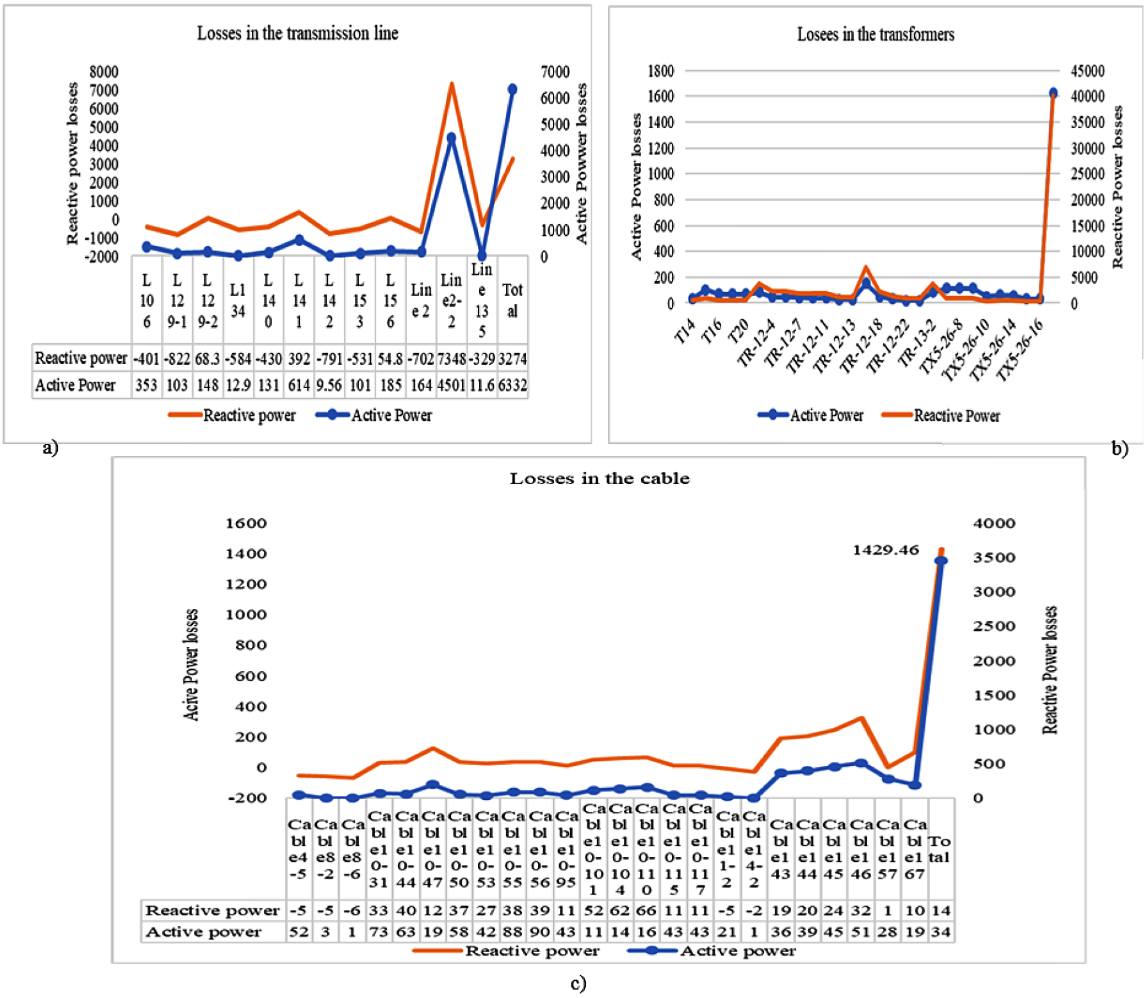

Figure 5. Power losses simulated into the part of power system of Kosovo (110/35/10/6 kV), a) overhead lines, b) transformers and c) cables

Shortcomings in seamlessly integrating of the simulated methods into the installed SCADA systems present a notable drawback to their overall performance. Therefore, there is a need for advancements in real-time data assessment, making it both timely and imperative for the optimization of power system operations. Addressing these challenges will not only enhance the effectiveness of the assessment methods but also contribute significantly to the overall efficiency and economic cost of power systems.

The simulated data reveals that the voltage profile on the 110 kV busbars of certain substations is lower when operating individually (wind turbine and PV) compared to when are integrated. In specific instances, the voltage drops to 106.6 kV, falling below the nominal value of 110 kV. This phenomenon is attributed not only to the losses occurring in SS Kamenica, where 106 MW of production is concentrated due to the involvement of PV systems and wind farms, also to the fact that the overhead line is linked with the other part of the system is the fully loaded. In essence, the discussion on transformers losses encompasses load characteristics, load coefficient, configuration the part of the system. Understanding these aspects is crucial when implementing remedial measures, as it not only impacts the enhancement of power transmission and distribution quality but also influences the transformers' lifespan.

Furthermore, based on the analysis, cable lines exhibit larger losses compared to overhead lines, attributed to their construction characteristics, distribution, and loading coeficient. Additionally, elements such as converters, inverters DC/AC, and other control systems of the photovoltaic contribute significantly to the notable increase in active power losses. In the context of wind turbines, electrical losses stem from components integrated into their structure, including asynchronous/synchronous generators, control systems, gearbox and other related equipment.

The analysis of results using software systems tools and simulations highlights the significance of understanding losses in the examined components for effective system planning and configuration. This involves identifying losses in specific elements, including substations, transformers, lines, and the generation system. The simulation method utilized provides valuable insights and approximation of the results.

To attain more precise and rapid results, there is a need to implement advanced methods, such as; neural network systems or other intelligent approaches. These sophisticated methodologies promise enhanced accuracy and speed, making them crucial for monitoring and evaluating losses. Incorporating such advanced techniques is essential for optimizing decision-making processes in the planning and configuration of the power system in real time.

In this context of technological tools and infrastructure for the advancement and assessment of power losses, encompassing types of losses (fixed, variable), loads, network configuration, lines, transformers, and load concentration, finding effective methods involves a comprehensive analysis and also integration of these components. Addressing potential solutions requires a combination and examination of these elements to develop alternative approaches and apply the most effective ones.

Figure 6 provides a visual representation of the proposed neural network architecture outlined in this paper for the assessment and classification of power losses. The designed scheme aims to establish a structured and intelligent system, utilizing neural networks to enhance accuracy and efficiency in addressing the complexities associated with power loss assessment and management. This illustration in Figure 6 serves as a visual guide to understanding the architecture devised to tackle challenges and optimize the management of power losses within the discussed context.

This architecture comprises neurons as inputs, a hidden layer representing components, and outputs providing assessments. This neural network encapsulates the three crucial components of artificial intelligence architecture for assessing and elucidating losses, contributing significantly to development and technological advancement. The network's neurons consider parameters of various components, including resistive and capacitive inductive currents, voltages, and flows of active and reactive power indexed by $X(x_1, x_2, x_3, x_4, x_5, ..., x_n)$. In reflection, the Hidden Layer column incorporates the number of various components (cables, lines, transformers) indexed by $Y(x_1, x_2, x_3, x_4, x_5, ..., x_n)$ and defines the discovered

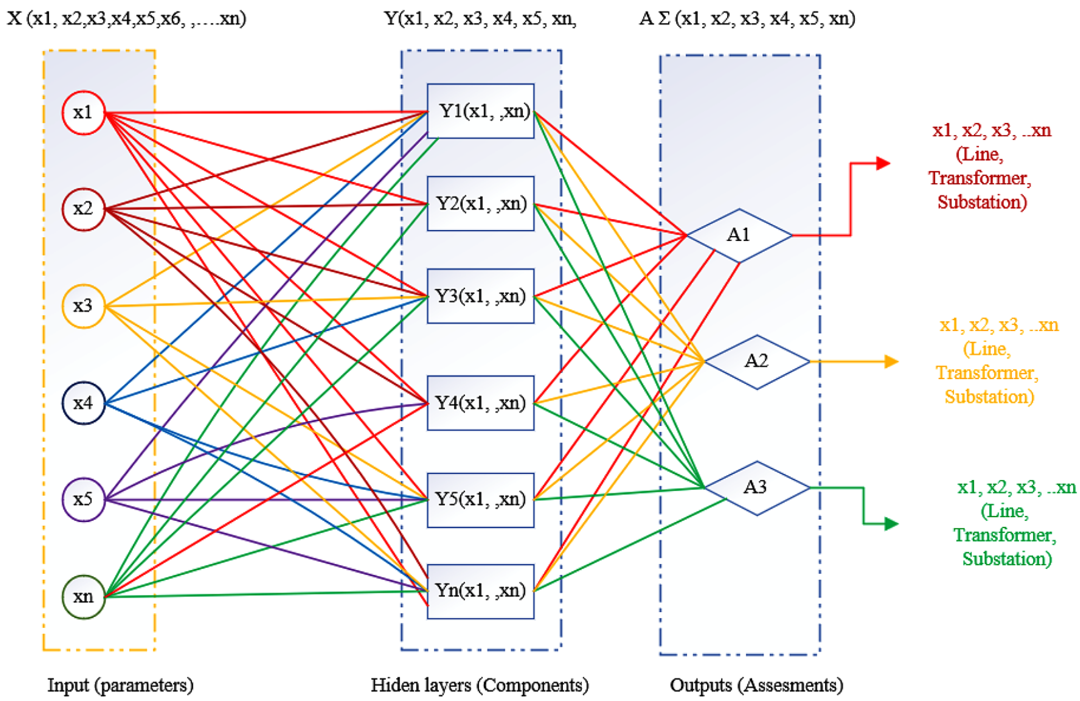

Figure 6. Proposed neural network architecture for power losses assessment and classification

values of losses for respective components. The outputs (Assessment) are listed in the last column of the proposed scheme's hierarchy, corresponding to indices (A_1, A_2, A_3, ..., A_n), identifying components with the most noticeable losses, their type, value, and economic cost. This approach offers insights and opportunities for online access, monitoring, and control of losses in network components, contributing to an overall enhancement in the power system's performance. The practicality and optimistic outlook make it a promising avenue for further exploration.

CONCLUSIONS

The analysis of the losses in the power system is a multidimensional task, encompassing optimization, ways of their reduction, management, and real-time evaluation. The paper encompasses an overview of loss assessment using simulation methods, providing a comprehensive summary of losses across power system components as part for the simulation and modeled, including lines, transformers, and the generation system involving wind turbines and PV systems. This approach serves as a solid method for identifying and calculating losses in these components, offering significant results that serve as a reliable basis for comparison with other real-time methods. This aids in the study and planning of the network at various evaluation stages in alignment with their specific objectives.

The evolution of intelligent evaluation methods holds substantial weight, given their precision and speed in processing data for real-time assessment and monitoring of losses in the electric power system. The paper, recognizing the importance of real-time loss assessment for each component, introduces an approach and proposal for assessment and monitoring through neural networks. This not only enhances the efficacy of loss management and optimization but also provides convenient opportunities for operators in Control Centers within Transmission Systems to optimize and enhance system performance through loss reduction and management.

The management of losses through this method, among other benefits, contribute to the reduction of the economic cost of Transmission Systems, impacting the voltage profile as well. The integration of intelligent methods into SCADA systems constitutes a significant enhancement for power systems. This method not only enables the optimize power flows, also increase the effective monitoring of power systems, and the achievement of the most accurate results in managing various components and power sources.

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